THE ENVIRONMENTAL IMPACT OF METRO EXPANSION ON AIR QUALITY IN BEIJING, CHINA

A Thesis

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ABSTRACT

Air pollution has been a very serious problem in China, and a significant portion of the pollution comes from the automobiles. Expansion of the public transportation system can potentially alleviate pollutions by diverting travelers from their vehicles. In this study, we conduct a spatial analysis to quantify the impact of subway expansion on air pollution in Beijing. The data we use consists daily monitor level Air Pollution Index (API) during 2008 to 2012, and spatial data of the geographic location of 27 monitors and 127 subway stations. We use the difference-in-difference approach for the analysis and divide the monitors into two groups based on their closest distances to the newly opened subway line. We find that after the subway opens, the API decreases significantly by 20.9% within a 30-Weekday window. The reduction effect on API maximizes at the first 10 weekdays after opening and fades out after 60 weekdays.

BIOGRAPHICAL SKETCH

Lin Yang was born in Mengzhou, China in 1992. She received her bachelor degree both from the Department of Agricultural and Resource Economics at the University of Maryland in 2014, and the Department of Economics and Management at China Agricultural University in 2015. She then started her Master's degree at the Dyson School of Applied Economic and Management at Cornell University from August 2014. During her graduate study at Cornell University, she focused on the research of environmental economics and transportation policy in China.

To my beloved family.

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1 Introduction

In the past decade, China has undergone rapid economic development and expansion in its automobile market. From 1980 to 2011, the per capita GDP of China increased hugely from less than $200 to almost $5500 in nominal terms according to the World Bank. Simultaneously, the transportation sector has become one of the dominant contributors to the air pollution. Among all the air pollutants, the chemical particulates emitted from automobiles, such as PM2.5 and carbon oxide have been well acknowledged as the most harmful pollutants to human health. The adverse health consequences caused by the air pollution exposure has drawn the attention of the public. According to a report released by the World Health Organization, in 2012, around seven million people died, one in eight of total global deaths, as a result of air pollution exposure.

Large traffic volume causes not only air pollution but traffic congestion, which leads to a large welfare loss. Currie and Walker (2011) estimate the welfare loss of $577 million per year caused by traffic congestion in the United States. China has largely devoted itself to the construction of transportation infrastructures, such as bus and subway systems to deal with the traffic congestion and air pollution issues. Motivated greatly by the following observations, we conducted this empirical study to quantify how does one major transportation infrastructure, subway system, benefit air quality in Beijing.

As the capital city, Beijing has experienced a rapid expansion of its population, car ownership, and transportation infrastructure. For instance, from 2001 to 2014, the population of Beijing increased by 55.6 percent from 13.83 million people to 21.52 million people. For the car ownership, in 2013, metro Beijing has more than four million private passenger cars. That’s 45% more passenger cars than are registered in Harris County, Texas, home to car-crazy Houston and several of its major suburbs. (China SignPost) During the same period (2001-2014), the transportation infrastructure in Beijing was largely invested and constructed: the total length of road increased by 2.25 times; the subway length increased by 8.74 times, and the total transport infrastructure investment increased from 15 billion RMB to 53 billion RMB. Average passenger volume of Beijing subway has increased hugely along with the subway expansion, with the average daily passenger volume reached 9.3 million in 2014, and the highest daily volume reached 11.5 million. These rapid expansions provide us possibilities to examine the impact they have on air pollution.

Along with the rapid urbanization and economic growth, the air pollution level in Beijing is deteriorating. Figure 1 gives the average PM2.5 densities in Beijing during the past years. The pollution levels in Beijing has a distinct upward trend overall, with a slight decrease between 2011 and 2012. The average level is about twice the Chinese annual standard, and six to ten times the U.S. annual standard. To deal with the pollution, the Beijing government legislates several air pollution treatment regulations such as driving restrictions, a lottery system for license plates allocation, closure or relocation of the heavy polluting plants and forbidden burning of low efficiency fuel. Although the strict regulations on heavy-duty vehicles and the bidding system in the allocation of the license plates contribute to the drop in average PM2.5 in 2011 and 2012, the air pollution in Beijing still remains at a high level. During the year of 2014, the Beijing government still issued 18 heavy pollution alerts. The serious situation of the air pollution in Beijing motivated us greatly to conduct this study.

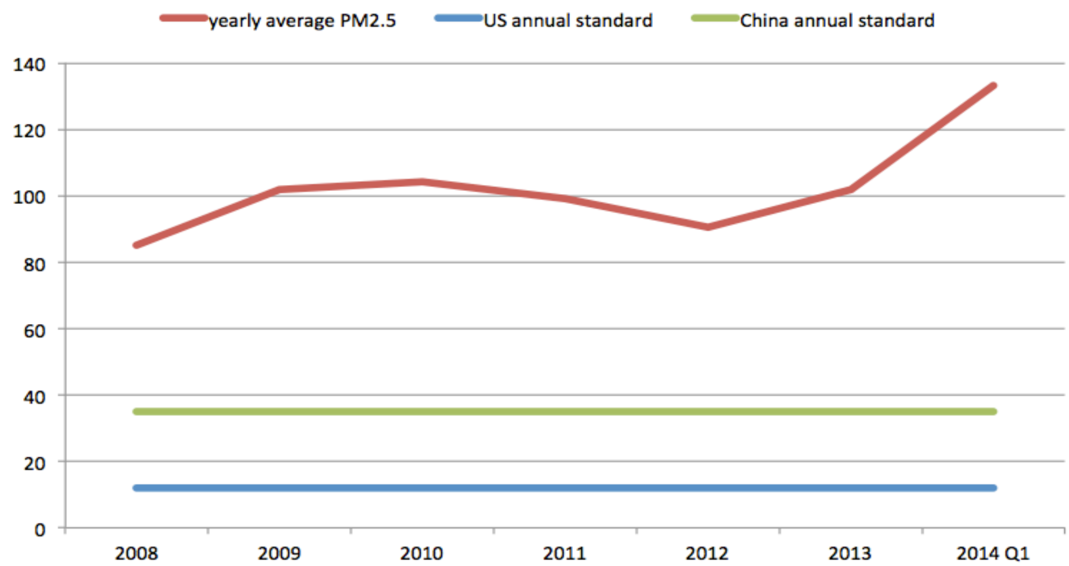


Figure 1. Beijing yearly average PM2.5 Density (ug/m^3) from US Embassy monitor

With the existing situations of Beijing, the study of the correlation between transportation infrastructure and air pollution has tremendous practical relevance. A basic theoretical assumption is needed in the examination, which is that the subway expansion leads to the reduction in automobile travelers, which in turn reduce the transportation-originated air pollution. Mohring (1972) examined a similar argument to our assumption, which was called the Mohring effect. The "Mohring Effect" implied that investments in rail transit infrastructure divert marginal automobile travelers away from their vehicles, resulting in a traffic diversion effect, and thereby reduce air pollution. However, different scholars have different opinions on this assumption. Vickrey (1969) argues that investments in transportation infrastructure simply induce demand for travel, resulting in a traffic creation effect. Duranton & Turner (2011) introduce the concept of induce demand in their paper, which examines the correlation between lane kilometers of roads and vehicle-kilometers traveled in US cities. They conclude that increased investment in roads or public transit is unlikely to relieve congestion.

The current literature studying public infrastructure development in Beijing mainly focuses on its correlation with housing value, and traffic congestion issues. Literature in the study of the relationship between the subway and air pollution is limited. Chen et al (2012) conduct a study that is similar to ours. Chen et al (2012) quantify the effects of one major type of transportation infrastructure—urban rail transit—on air quality using the sharp discontinuity in ridership on an opening day of a new rail transit system in Taipei. They find that the opening of the Metro reduced air pollution from one key tailpipe pollutant, carbon monoxide by 5 to 15 percent. Different from Chen et al (2012), we focus on five subway lines opened between 2008 to 2012 in Beijing, and conduct a spatial analysis following the strategy used in Viard and Fu (2012).

The major empirical challenge in quantifying the causal effect between subway system expansion and air pollution comes from the confounding factors that have a correlation with the subway system, and the unknown factors or chemical processes that may result in the fluctuation in pollutants' density. For example, there exists a special correlation between the choice of the location of the subway stations, and the traffic volume nearby. City planners tend to build the subway stations in areas where the travel demand is the largest, which means the amount of cars passing through may also be large at all times. That is the reason why on some days when the utilization of the subway is especially high, the traffic volume and air pollution are similarly elevated in the area. The existence of the confounding factor and the complicated fact of the public infrastructure policy forces us to find a credible identification in order to accurately estimate the correlation between public infrastructure and air quality. We tackle this challenge by exploiting exogenous variations from the opening of a new subway line.

The data we use consists of the following. The first dataset we collect is the monitor-level daily Air Pollution Index (API) in Beijing from 2008 to 2012. Second, we calculate the distances between each pair of the twenty-seven monitoring stations and subway stations in five subway lines opened during the sample period. Based on the locations, we divide the monitors into different groups for further examination. We also collect data on a set of control variables. We control for daily weather variables such as wind speed, wind direction, temperature, special weather condition (fog, snow, storm, rain), and more, as well as the lagged weather variables for one and two days before. We also have knowledge on the last digit numbers of the license plates that are restricted on each weekday, which directly correlate to the number of vehicles on road.

We adopt the Difference in Difference method and divide the 27 air quality monitors into two groups based on their closest distances to the newly opened subway line. We define the monitors that are located inside of 2km distance range of the subway lines as the treatment group, and the monitors that are located outside of 20km distance range as the control group. Due to the fact that particulate matter's ambient properties dictate that it is deposited within a few kilometers of its release (Viard & Fu, 2012), the spatial location of an air quality monitor matters. Our underlying assumption is that, in absence of the subway opening, the trends of API during a short time period around the opening dates for the two groups should be similar. More precisely, air pollution levels in Beijing on the days just before the subway lines' opening provide a valid counterfactual for air pollution levels on the days just after the opening dates, conditional on the differences in the control variables such as weather and driving restrictions.

Our research reveals the following results. First, we find that the opening of new subway stations reduces API significantly. Our standard DD estimation indicates that the API measured by the treatment group decreases by 20.9 % after a subway line opens within the 30-weekday window, with a buffer zone of (2, 20] km. Second, according to the extensions of standard DD, we find that there exists heterogeneous effect in both the distances between monitors and subway stations, and the time periods after subway opening. The pollution reduction effect of subway opening reaches its maximum at the first ten weekdays after opening, decreases gradually after 30 weekdays, and tends to fade out after 60 weekdays, which might be explained by the adjustment of the commuters' travel behavior.

The principal contribution of our study is to provide a rigorous quantitative analysis by using the spatial information as our identification. It adds to the limited literature in air pollution and public infrastructure, and answers indirectly to the controversial question of how much does the automobile contribute to air pollution.

The following paper is organized as follows. Section 2 discusses the institutional background and related literatures. Section 3 introduces the facts of the data and presents the summary statistics. Section 4 describes the empirical model adopted and the primary results. In Section 5, we discuss the policy implications and the limitations of this study and Section 6 concludes.

2 Background and literature review

As stressed above, the expansion of Beijing subway system gives us enough variation to conduct this analysis of the causal effect between transportation infrastructures and air pollutions. With the serious air pollution problem, it is also necessary to discuss the regulations and policies in transportation sector. In this section, we introduce the institutional background of the fast expansion of the Beijing subway system, and the relative transportation regulations in Beijing. Also we introduce the relevant literatures.

2.1 Beijing Subway System

The Beijing subway system does not have a long history, but it was the fast expansion that caused attention. The subway was first proposed in 1953 by the city's planning committee and experts from the Soviet Union. For the purpose of both civilian and military use, after experiencing technical obstacle and nature disasters, the first subway line's construction finally began on July 1, 1965. After four years' construction, Line 1 opened in 1969.

For over 30 years, there were only two subway lines serving the whole city. After China won the bid for holding the 2008 Olympic Games in 2001, the rapid expansion of Beijing subway system was brought on by Chinese government in order to serve the huge amount of tourists, and relieve the pressure on traffic.

As shown in the subway expansion timeline (Figure 2), 16 new metro lines were opened in twelve years starting from 2002. By the end of 2015, there were a total of 18 operating lines including seventeen subway lines and one airport line. The system now has track with a total length of 554km and 334 subway stations, covers eleven districts, and is the second longest subway system in the world after the Shanghai Metro.

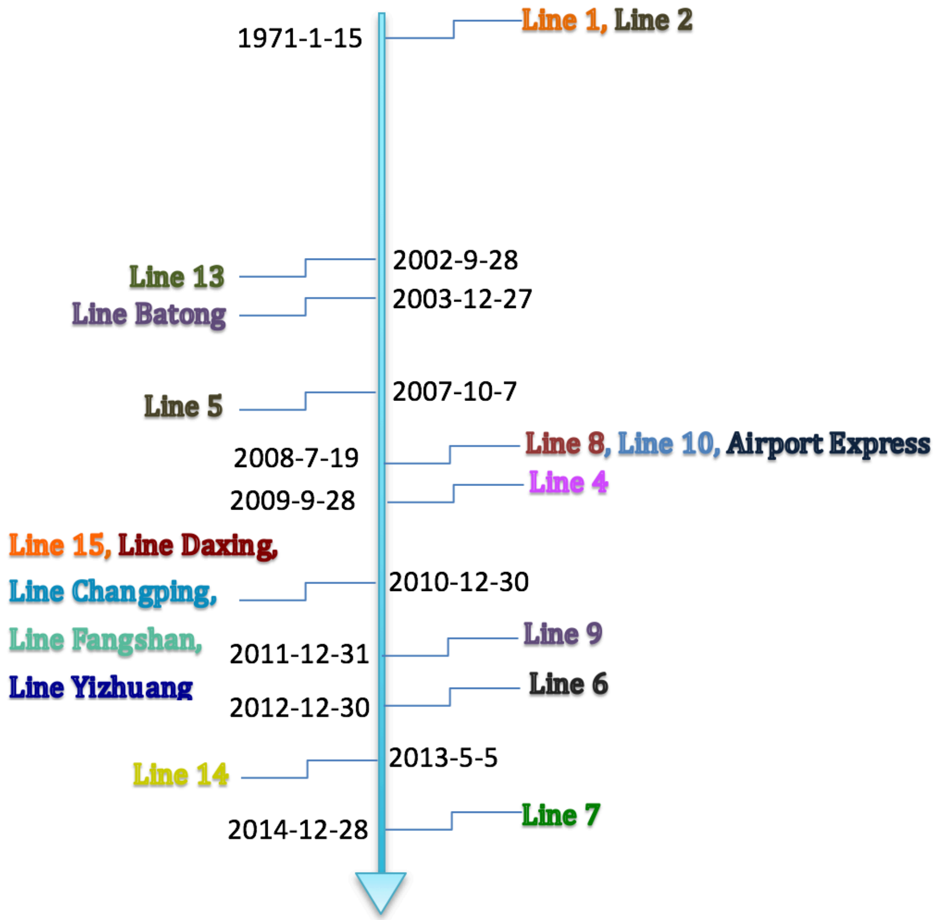


Figure 2. Beijing Subway Expansion Timeline

Besides the time variation that many researchers focus in their paper, the spatial variation caused by subway expansion is non-negligible. Beijing is a city with 16 urban, suburban, and rural districts. The expansion of the subway system was designed to gradually cover as much area as possible, for the convenience of the citizens, and for the largest traffic divergence possible. As the subway lines increases, the distribution of the subway stations' location changes. Taking advantage of the spatial variation, our research idea stands out from the similar research in the impact of public infrastructure on air quality.

2.2 Relative Regulations in Beijing

In the past decades, the Chinese automobile industry has grown to the largest in the world with a total output of over 18.5 million units including 14.5 million passenger vehicles in 2011(Li, Xiao & Liu 2014), and the automobile sales has seen a five x growth in the last ten years. Figure 3 shows the vehicle sales development in China since 2005. In 2005, approximately 6 million vehicles were sold in China; while in 2011, China's automakers set new record of sales by an annual sale of 18 million new vehicles, 205.08% more than 2005, and surpassed the record of 17.4 million units' annual sales set by the U.S. in 2000.

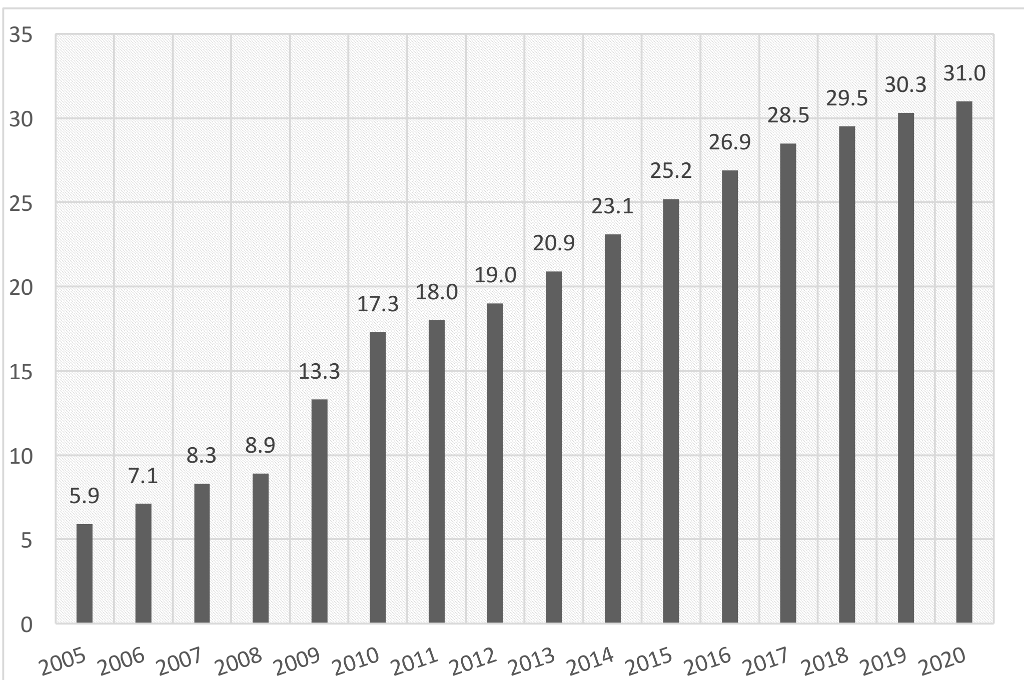


Figure 3. Vehicle Sales Development in China, Millions of Units, 2005-2020 (predicted)

The Beijing government has taken several measures in order to control the air pollution caused by the increasing car ownership. The first restriction set on driving cars is a restriction on the right to drive based on the last digit of the license plate. In general, the restriction is that, each day certain two numbers will be restricted during 8am to 8pm.

During the 2008 Olympic Games period, also when the air pollution is extremely bad, like the days in Dec 2014 when the government issued the first "red alert" ever on air pollution, the restriction is based on odd or even number.

The driving restriction does slow down the increasing trend of air pollution significantly, Viard and Fu (2012) find that traffic restriction led to a 19% decline of API during every-other-day restriction and a 7% decline during one-day-per-week restriction. This is consistent with the findings of Chen et.al (2013), who examine the effectiveness of different environment measures China government adopted to prepare for the 2008 Olympic Game. However, under the strong desire of driving, Beijing citizens come up with a "solution" to deal with the restriction, that is to buy a second car. We can also see a similar trend from Figure 2 that, from 2008 to 2009, the vehicle sales in China sees the largest increases by 49.44%. To deal with the increasing vehicle sales, Beijing government adopted automobile license quota systems in major cities to control the increasing ownership of vehicles. A lottery system was adopted in Beijing for the license plate allocation since 2011. The possibility of getting a license plate in Beijing has decreased from 1:10 to 1:100 as the number of licenses allocated is restricted year by year. As shown in Figure 3, the increasing rate has decreased significantly after 2011. However, given the large population base and the existing automobile ownership, there will be a lag before the increasing trend will be affected. The traffic congestion issue in Beijing is still persistently influencing citizens' daily life, so the air pollution problem remains.

2.3 Other literatures

Papers that study the correlation between driving restrictions, public transit and traffic congestion or air pollution in other countries include David (2008), who study the effectiveness of driving restriction in Mexico City, however, the results show that the driving restriction in Mexico City does not contribute to improvement in air quality and people tended to buy more cars instead of substituting to low-emissions public transportation; Anderson (2014) examines a strike in 2003 by Los Angeles transit workers and finds out that the contribution that public transit have made to relieve the traffic congestion is actually underestimated. Lin et al. (2011) investigate the effectiveness of the driving restrictions in the cities Sao Paulo, Bogota, Beijing and Tianjin.

Most of the studies look into the impact of public transit or transportation regulations take the Regression Discontinuity approach, except Viard and Fu (2012), who use the Difference in Difference as their main approach.

The following literatures use spatial factor such as variation in distance for DD identification. First, Schlenker and Walker (2012) study the impact of airport congestion on local air pollution in areas downwind and upwind of airports. Second, Currie and Walker (2011) examine the response to toll traffic changes based on distance from toll plazas. Third, Hanna and Oliva (2011) study the impact of factory closure based on distance to the erstwhile factory.

Based on our research assumption, the reduction in API is contributed by the reduction in the traffic volume which is a possible consequence of opening a new subway line. The effect on air quality is not a direct result of the subway opening, so we do not expect to see the effect of reduction in either the traffic volume or the air pollution immediately at the day of opening. In another word, our research design is not based on a discontinuity at the threshold (subway opening), which is the basic setting in RD. For example, Chen et.al (2012) take advantages of the discontinuity in ridership at the opening date of the subway line in Taipei. Our study instead, is the most similar with Viard and Fu (2012) in terms of the main methodology, which uses the difference in distances as identification.

3 Data

Our empirical analysis is based on high-frequency data on both air pollution and weather conditions, as well as the spatial data for monitors and subway stations. We exclude all weekends and holidays because of the inconsistency in driving regulations and uncertainty in commuters driving demand.

1. Air Pollution Index

In order to examine the relationship between subway expansion and air quality, we choose the daily Air Pollution Index to represent the air quality condition. The Air Pollution Index is a simple number that shows the level of air pollution in this city or area, and is based on five atmospheric pollutants, sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates (PM_{10}), carbon monoxide (CO), and ozone (O_3) measured at the monitoring stations throughout each city. The pollutants that Chinese government take into account in Chinese API are the first three. The mechanic of measuring the API level is that an individual score is assigned to each pollutant based on their levels, and the final API is the highest of the three pollutant scores[1] (The standard of scoring each pollutant is showed in Table 1). Statistics of API from 2000 to 2010 shows that, during the decade, there are 1196 days that the inhalable particulate matter -- PM10 is the dominant air pollutant. That is around 96.76% of all air pollution days. Note that the Air

[1] Suppose in an area, the mean PM10 density is 0.215 mg/ m^3, the SO_2 density is 0.105 mg/ m^3, the NO_2 density is 0.08 mg/ m^3. Then the score assigned to PM10 is calculated as follows: According to Table 1, the PM10 density 0.215mg/ m^3 belongs to 150 μg/m^3 - 350 μg/m^3, which is 0.15 mg/ m^3 -0.35 mg/ m^3, according to the correspondent API range 100-200, the PM10 score I is: $I = ((200-100) / (0.350-0.150)) * (0.215-0.150) +100=132$

Thus, I=132 (PM10); I=76 (SO2), I=50(NO2). The area's API for that day is the largest score among all the air pollutants: API = max (132,76,50) =132, and the major air pollutant is PM10.

Pollution Index (used until 2012/12/31) does not take PM2.5 into consideration specifically, which is currently recognized as the most harmful air pollutants to human health. Based on the definition of PM10, which is the particulate matter that is less than or equal to 10 microns, data of PM10 should contain information about PM2.5. We can approximate the density of PM2.5 by the ratio of PM2.5 to PM10, which is usually between 0.5 to 0.8. (WHO 2005)

Table 1: Transformation from Pollutant Concentration to API

API	PM10 ($\mu g/m^3$)	NO2 ($\mu g/m^3$)	SO2 ($\mu g/m^3$)
0-50	0-50	0-80	0-50
50-100	50-150	80-120	50-150
100-200	150-350	120-280	150-800
200-300	350-420	280-565	800-1600
300-400	420-500	565-750	1600-2100
400-500	500-600	750-940	2100-2620

For Beijing, there are two types of API data that can be accessed through the government's website. One is the aggregate daily API released by the Ministry of Environmental Protection (MEP) of China. Another one is the station-level daily API released by Beijing Municipal Environmental Monitoring Center (MEMC).

The station-level API data is more preferred because of its objectivity. The aggregate API is a number combined from all monitoring stations in Beijing, and is more easily to be manipulated by the government in order to give the public a false impression that the air pollution problem in Beijing is not as bad as it appears. However, the station-level API is different numbers monitored by 27 different monitoring stations that are located all around Beijing. Since the monitors are located in different locations, the index they monitor would be more representative because different districts of Beijing are different in industry structure, population, traffic condition and other factors that can influence the air pollution level. In addition, the station-level API is released by MEMC which is more like an environmental protection agency than a government department, which means the data is more reliable.

Based on the standard released by Chinese government, there are six levels of air pollution condition, which are: 0-50, 51-100, 101-150, 151-200, 201-300 and more than 300. Taking the aggregate API and average of the station-level API from a same period, for example the year of 2009, we found that there are in total 283 days counted as "great" (0-50) or "good" (50-100) using aggregate API. However, when we average the station-level API and evaluate it using the same standard, the days that can be counted as "great" or "good" are only 271 days, which directly shows the government's manipulation on aggregate API data. As a result, we use the station-level daily API from 1/1/2008 to 12/31/2012, from 27 monitoring stations. The reason that we only use this five years' data is that during this period, the Beijing subway expanded rapidly, and because the Beijing government switched the index they used from API to Air Quality Index (AQI) from 1/1/2013.

2. Weather

Weather conditions are essential to the studies of air pollution issues. We apply an extensive set of controls for weather conditions including: average temperature, average wind speed, average relative humidity, average visibility, precipitation, dominant wind direction and dummy variables for days with special weather such as rains, fogs, storms and snow. Except for the wind direction data, which we acquire as hourly data, the other weather variables are daily. In order to make the hourly wind directions consistent in format with the rest of the dataset, we separate the wind into eight major directions, and generate eight dummy variables for each direction to indicate what is the dominant wind direction during each day.

In addition to the original weather variables, we also control for the lagged weather in order to cover the lagging impact of weather conditions on API. The difference between wind direction and the other weather variables is that the effect of wind on air pollutants takes place faster. Thus we include an 8-hour lag for wind directions, but a 1-day and 2-day lag for temperature, wind speed, humidity and precipitation.

Table 2. Descriptive Statistics

	Full Sample (1)	60 Weekdays Pre-Open (2)	60 Weekdays Post- Open (3)
Panel A. Air Pollution			
API Value	82.82	93.55	77.17
	[48.14]	[64.42]	[51.44]
Panel B. Weather			
Average Temperature (C)	12.60	15.47	9.96
	[11.62]	[10.36]	[11.74]
Average wind speed (Km/h)	10.90	9.74	10.67
	[5.59]	[5.07]	[5.99]
Average relative humidity (%)	43.68	51.53	44.73
	[21.37]	[20.53]	[22.35]
Total rainfall or snowmelt (mm)	11.26	12.62	11.27
	[19.79]	[21.8]	[19.44]
Number of Observation	163680	8040	8072

Panel C: Dominant Wind Direction

N	NE	E	SE	S	SW	W	NW
374	31	154	96	262	21	-	122
[30.91]	[2.56]	[12.73]	[7.93]	[21.65]	[1.74]	-	[10.08]

Note: The unit of observations is day for all variables. For Panel A & B, the main entries are the mean of each variable. The entries in square brackets report the standard deviation of each variable indicated in the row heading. For panel C, the main entries are the frequency of each dominant wind direction during all weekdays in 2008-2012. The entries in square brackets report the percentage of each dominant wind through out all weekdays in the sample period.

Table 2 above summarizes the descriptive statistics for the air pollution index and major weather variables. Summary for the full sample are presented in the first column. We also show the results for 60 weekdays pre-opening and post-opening in the next two columns.

3. Geographical Data

3.1 Air quality monitoring stations

As stated above, this paper will contribute to the similar literature by using spatial analysis. In addition to the air pollution data, the spatial data includes locations of the air quality monitoring stations and subway stations, and most importantly the distance between them. The spatial data is mainly captured from the Google Map and processed in ArcGIS. Figure 4 is the map which shows the distribution of the 27 monitoring stations, 11 stations are central government operated, and the other 16 stations are local government operated. Geographically, 8 stations lie within 5th ring areas and 19 stations are outside 5th ring areas.

3.2 Subway stations

Among the 11 lines opened between 2008 to 2012, the subway lines that we choose as the sample are Line 4, 8, 9, 10 and 15. Figure 5 is a map of all Beijing subway stations, from the context map and the extended box, we can see that most of the subway stations are distributed in inner districts of Beijing. The Beijing government has also developed the public transit for the suburb cities. On Dec 30, 2010, four subway lines targeting on the suburb cities were opened, which were Line Daxing, Changping, Fangshan and Yizhuang. Although these four suburban subway lines were also opened during the API data period, the number of air quality monitoring stations around these lines were too little to serve as qualified data sample. Thus, in order to get enough observations, we set our sample as only Line 4, 8, 9, 10 and 15. We also leave out the Airport Express line due to lack of observations.

Note that Line8 and Line10 are opened at the same day. Also, some individual stations which are numbered as a new part of Line 8 are opened at the same day with Line 9. Under this situation, we treat all the stations that are opened at the same day as one subway line but with more stations. So in the following paper, the analysis is based on the four opening dates, which are 2008/7/19, 2009/9/28, 2010/12/30 and 2011/12/31.

3.3 Distance

Based on our theoretical assumptions, the monitors that are located at different locations will be affected differently by the opening of the subway lines, so the distance between each monitoring station and its closest subway station on the new subway line is calculated using ArcGIS. Figure 6 shows the relative locations of Beijing air quality monitoring stations and subway stations in 2014. We can see that most of the subway stations are distributed centrally in the city of Beijing. On the contrary, the air quality monitors are distributed sparsely around the entire Beijing area, which seems to make the monitors that are in the suburbs good candidates for choice of control group. However, the other factors such as, factory placement, population density, geographic and topographical features in the suburbs are also quite different from the central area, which means we need to consider rigorously on the choice of control group. We will discuss more in the model section below.

Table 3. Summary Statistics for Distance

Line	Date	Mean	Std. Dev.	Min	Max
Line 4	09/28/09	30.919	27.997	1.35	99.65
Line 8 & 10	07/19/08	31.313	26.521	0.69	92.44
Line 9	12/30/10	24.217	18.104	0.64	69.31
Line 15	12/31/11	35.879	20.809	5.51	81.98

During the data period of API (2008-2012), the locations of monitors did not change, so the variation in distance comes from the subway expansion only. From the summary table above (Table 3), we can see that for the five sample subway lines, the average distance between a monitor to the closest subway station ranges from 24km to 35km, with the smallest distance as 0.64km and the largest as 99.65 km.

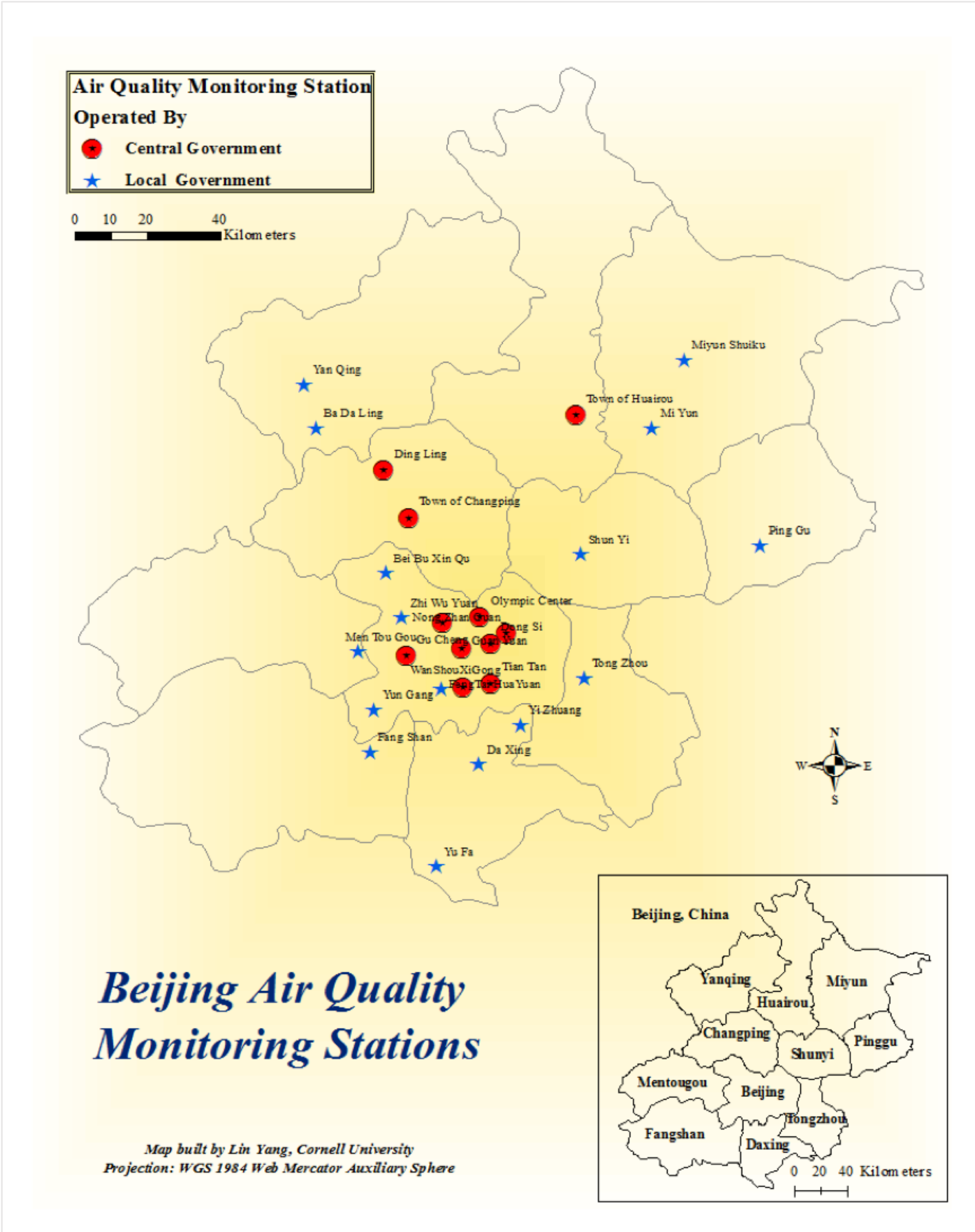


Figure 4. Beijing Air Quality Monitoring Stations [2]

[2] See Appendix C for the relative locations of the air quality monitoring stations and the ring roads in Beijing.

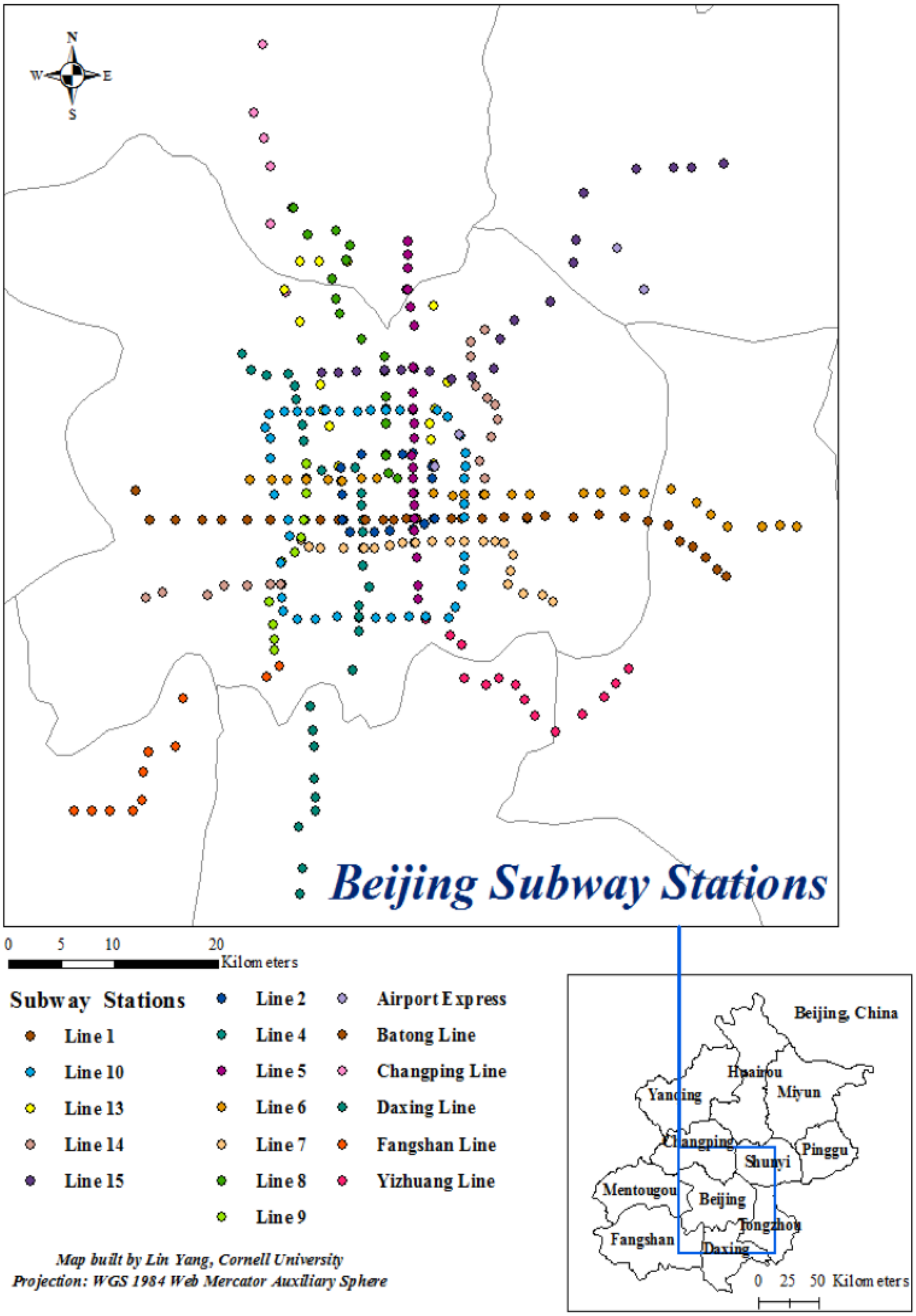


Figure 5. Beijing Air Subway Stations in 2014[3]

[3] See Appendix C for the map of the five subway lines in sample.

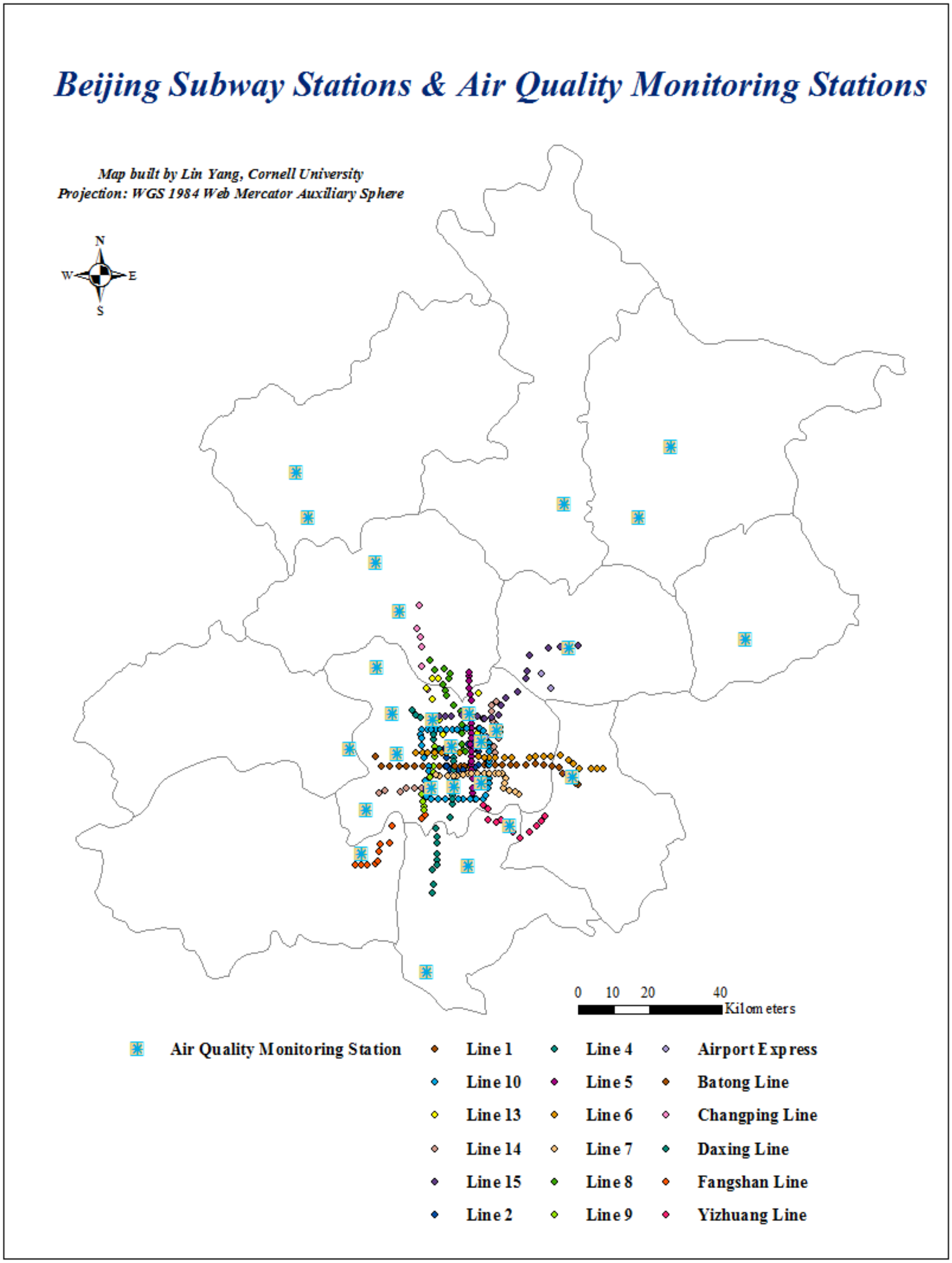


Figure 6. Locations of Beijing Subway Stations and Air Quality Monitoring Stations in 2014[4]

[4] See Appendix C for the map of the five subway lines in sample.

4 Empirical methods and results

In this section we introduce the empirical models we use and the primary results. This study is designed based on the Difference-in-Difference (DD) approach, in order to eliminate the impact of confounding factors that affect all monitors before or after the subway opening. We first develop a basic DD model using distance as identification, and regard monitors that are located further than 20 km from the new subway lines as the control group.

4.1 Standard Difference-in-Difference

The basic Difference in Difference model we adopt in this study is

$$y_{it} = \theta_0 + \theta_1\, Open_t + \theta_2\, Within2_{it} + \theta_3\, [Open_t \times Within2_{it}] \\ + \theta_4 \boldsymbol{x}_t + \xi_t + v_i + \varepsilon_{it} \tag{1}$$

$$\boldsymbol{x}_{it} = \boldsymbol{\delta}\, \boldsymbol{Weather}_t + \boldsymbol{\sigma}\, \boldsymbol{Weather}_{t-1} + \boldsymbol{\rho}\, \boldsymbol{Weather}_{t-2} + \boldsymbol{\mu} \boldsymbol{DrivingRestriction}_t \\ +\ \alpha_1\, SubwayStation5_{it}$$

where the outcome variable is $\ln(API)_{it}$, which is the logarithm of Air Pollution Index measured by monitor *i* at time *t*. $Open_t$ is an indicator variable that takes a value of one for the dates after the five subway lines are opened and a value of zero for the dates before each subway line is operational. The second dummy variable $Within2_{it}$ equals to one if the monitor *i* belongs to the treatment group at time *t*.

The interaction term in the DD model is the one we are mostly interested in. The parameter of interest in this specification is θ_3. Here the interaction variable

$Open_t \times Within2_{it}$ captures the difference between the treatment group and the control group and the difference in air pollution level before and after the subway opening.

$\boldsymbol{x}_{it}$ includes the set of controls we have. As introduced above, we control for the variation across the time in weather conditions by adding in nine weather variables, which include average temperature, relative humidity, wind speed, precipitation, visibility and four indicators for the special weather such as snow, rain, storm and fog. The wind direction is controlled by eight indicators for the dominating wind directions. We also include 1-day lags and 2-day lags of the first four weather variables in order to control for the lagged effect of weather conditions on air pollution level. The model also includes ten indicators for each number from 0 to 9 that is restricted at time *t* as the last digit of license plates. The time invariant effect is controlled by the monitor fixed effect (FE) υ_i. ξ_t is the year-month FE and ε_{it} is the error term, which is clustered by each day to allow correlation across monitoring stations in one day.

We also add the number of subway stations that are located within 5km around each monitor, and its interaction with $Open_t$. We would like to loose the assumption that when each subway line opens during the five years, the effect on air quality is the same regardless of the order. Since the subway system is a network, the subway lines nearby work together to serve a certain area. That is why we need to control more factors in order to account for the heterogeneous effect in the opening of different subway lines. For example, suppose there is only one subway line that is located within 5km area from both monitor1 and monitor2. Once a new subway line opens within 5km from monitor1 but not monitor2, there will be two subway lines accessible to monitor1. Then the environmental effect of the new subway line captured by monitor1 and monitor2 will be different. For the number of subway stations on each new subway line that are located within a certain distance area from the monitors (here we use 5km as an example), the intuition is similar with the number of subway lines. Instead of the network effect of different subway lines, the number of subway stations nearby account for the difference in the ability that different subway line can serve within a certain area. So we control for the number of subway stations within 5km ($SubwayStation5_{it}$), no matter which subway lines the stations are on, to account for both the network effect and the accessibility of each subway line.

Rationale behind the choice of treatment group (2km) – Assume that the residents who are not benefited by the newly opened subway line keep the same transportation behavior, such as the transportation type and the route of commuting. The variation in the subway ridership will be correlated with the passengers which is the group of residents who are benefited who live near the new subway line. Thus the radius of the area that a subway station can be easily accessed to is crucial to our research.

A common length of time that people would like to travel to a subway or bus station is about 5-15 minutes, according to the survey and literature about the accessibility of public infrastructure. The average walk distance, based on an average walking speed of 5km/h, is less than 1km. There is also another travel mode that people commute between residences and public transportation stations in China. A lot of residents choose to ride bikes to take the subway. Based on an average biking speed of 18km/h, the average travel distance in 5 to 15 minutes is about 3km. Because the average travel distance considering both types of commuters is around 2km, we choose 2km as the dividing point. Since this is just a rough approximation, we also provide the results of standard DD using different distances as the dividing point in Appendix B.

Buffer Zone – We set the area between 2km to 20km away from the subway lines as the buffer zone. Since the transportation system is a network system, for both ground transportation and underground rail transit, the monitors that are just a little further away will also capture the impact of subway opening on air pollution. Thus the monitors that are located in the buffer zone may not form as valid counterfactuals for the treatment group. We also verify this argument by the pre-opening common trend test described in the next subsection. Note that even if the monitors in the buffer zone may serve as a valid control group, there might be other unobservable factors existing that can impact the accuracy in our estimation.

Figure 7 shows the average environmental effect of subway openings when using monitors outside of 20km as the control group. In order to make the graph reasonable and consistent with our specification, we control the weather factors and all the fixed effects for the data points, and draw the trend from the residuals. From this graph, we can have a general idea of the API trend for both groups pre-opening and post-opening without running the regressions. Overall, the difference between treatment and control group is obvious. The trend of API pre and post opening for the control group is constant. However, the trend for the treatment group changes from above the control (pre-opening) to below the control (post-opening), indicating that there does exist an environmental beneficial effect of subway opening. The parallel trend for the treatment and control group is also observable. However, more precise test needs to be done in order to validate the most important assumption in DD study.

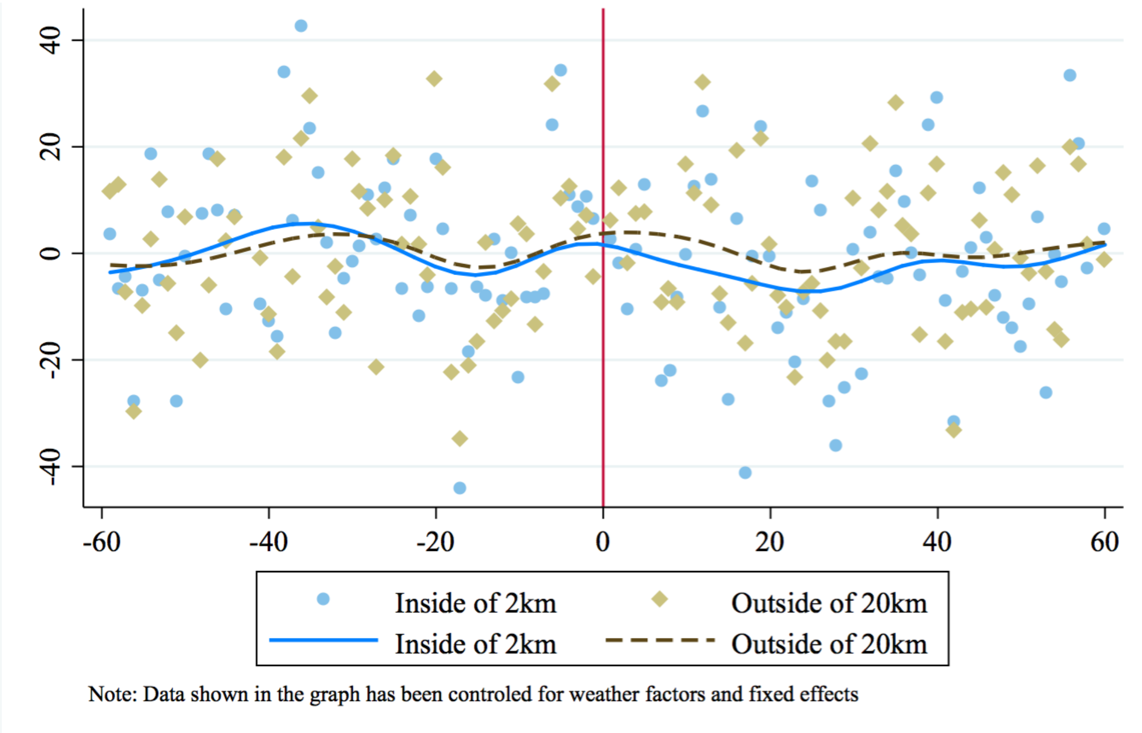


Figure 7. Average Effect of Subway Opening on API (%) in 60 Weekdays Window For Monitors Inside of 2km Vs. Outside of 20km

4.2 Test of Parallel Trend Assumption

Prior to the basic model, we test the most important assumption for DD – the parallel trend assumption.

$$y_i = \theta_0 + \sum_{m=1}^{5} \delta_m before_m + \theta_2\, Within2_{it} + \sum_{m=1}^{5} \rho_m before_m \times Within2_{it} \qquad (2)$$

$$+\theta_3 \boldsymbol{x}_t + \xi_t + v_i + \varepsilon_{it}$$

We restrict the sample to be 60 weekdays before subway openings, and divide the 60 days into six pre-treatment periods, represented by $before_m$. The theoretical idea in this model is that we include the interactions of the time dummies and the treatment indicator and leave out the interaction for one of the pre-treatment periods due to multicollinearity.

We expect to see the insignificance of all the interaction coefficients, which shows that there is no significant difference in the effect on API between treatment group and control group before the subway openings. Similar to the DD specification before, we leave the distance range of (2-20] km, (2-15] km, (2-10] km and (2-5] km as the buffer area respectively, and also examine the case of no buffer area at all.

Table 4. Test of Pre-treatment Parallel Assumption

Ln(API)	Control: >20km	Control: >15km	Control: >10km	Control: >5km	Control: >2km
Within 2km * (0,10] weekdays before	-0.0077	0.0179	-0.0178	0.0098	0.0059
	(0.0459)	(0.0446)	(0.0455)	(0.0396)	(0.0383)
Within 2km * (10, 20] weekdays before	-0.0028	0.00749	-0.0342	-0.0009	-0.0030
	(0.0465)	(0.0434)	(0.0458)	(0.0386)	(0.0376)
Within 2km * (20,30] weekdays before	-0.0266	-0.0120	-0.0490	-0.0201	-0.0233
	(0.0459)	(0.0422)	(0.0415)	(0.0375)	(0.0364)
Within 2km * (30,40] weekdays before	0.0655	0.0816*	0.0474	0.0749*	0.0697*
	(0.0460)	(0.0440)	(0.0431)	(0.0406)	(0.0391)
Within 2km * (50,60] weekdays before	0.00317	0.0340	-0.0327	0.0327	0.0313
	(0.0558)	(0.0516)	(0.0499)	(0.0492)	(0.0481)
Observations	3,647	4,372	4,785	5,468	5,674
R-squared	0.715	0.724	0.725	0.730	0.731

Note: Each column reports the result from one regression using different sets of controls when fitting equation (2). All have controlled for the monitor FE, year-month FE, Day of week FE, weather & lagged weather variables, and driving restriction dummies. Cluster SE by each day in parenthesis.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10%level.

Table 4 shows the result of the test of pre-treatment common trend assumption. We test different sets of control groups with monitors outside of 20 km, 15 km, 10 km, 5km and 2 km (No buffer zone). The purpose of the test is to testify the validity of our choice in control group, and the necessity to set the (2-20] km buffer area.

From the test results, we can clearly see that the control group with monitors outside of 10km and 20km are the ones with insignificant estimations for all periods, which indicates that the monitors that are located outside of 10 km or 20km away from the subway lines can serve as valid counterfactuals for monitors in the treatment group (within 2km). We take the monitors that are outside of 20 km as our control group as an example and put the results of using (2, 10] km as buffer zone in the Appendix for reference. Figure 7 above also provides an evidence of the similar trends for the treatment group and control group from the raw data.

Table 5. The Effect of Subway Opening on API (%): Standard DD Estimates

Control Group:	>20km	>20km	>20km	>2km
	(1)	(2)	(3)	(4)
Ln(API)	DID	DID	DID	DID
	(30Days)	(60 Days)	(90 Days)	(30Days)
1(Distance<= 2km)	-0.00517	-0.0283	-0.00734	0.0444***
	(0.0344)	(0.0217)	(0.0170)	(0.0152)
1(Subway Opening)	0.0347	0.0338	0.0105	0.0163
	(0.129)	(0.120)	(0.107)	(0.134)
1(Open) * 1(Distance<=2km)	-0.209***	-0.116***	-0.0777***	-0.105***
	(0.0455)	(0.0304)	(0.0239)	(0.0226)
Constant	4.417***	5.951***	6.149***	4.424***
	(0.550)	(0.378)	(0.241)	(0.552)
Observations	3,729	7,367	11,024	5,835
R-squared	0.702	0.650	0.634	0.708

Note: Each column reports the result from one regression. All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. Column 1-3 report the coefficient estimates by using monitors outside of 20km as control group, and using 30-Weekday window, 60-Weeksay window and 90-Weekday window respectively. Colum 4 reports the coefficient estimates by using monitors outside of 2km as control group and in 30-weekday time window.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5 presents the estimation results from four regressions with different sets of controls and different time windows, from fitting equation (1) above. With the dependent variable as the log of API, the coefficients stand for the percentage change in API. The results in Table 5 indicate that the opening of the subway lines contributes significantly to reducing

API. The results also prove the importance of the buffer zone. Taking 30-weekday window as an example, with (2, 20]km buffer zone, the environmental reduction effect of subway expansion is 20.9%; however, without the buffer zone, the reduction effect is 10.5%, which is underestimated. We can visualize the pollution reduction effect easily from Figure 7, the blue polynomial line drops after the opening date, while the dashed line of the control group remains at the same level as before. The difference in the coefficients between the 30-weekday window and the 60-weekday window shows a consistent trend with Figure 7, the two lines get closer to each other after the 30th weekday. The results in Table 5 show that the pollution reduction effect in 30-weekday window specification is a little smaller than the twice of the coefficient in the 60-weekday window, which also indicates the decreasing of the effect after 30 weekdays of opening.

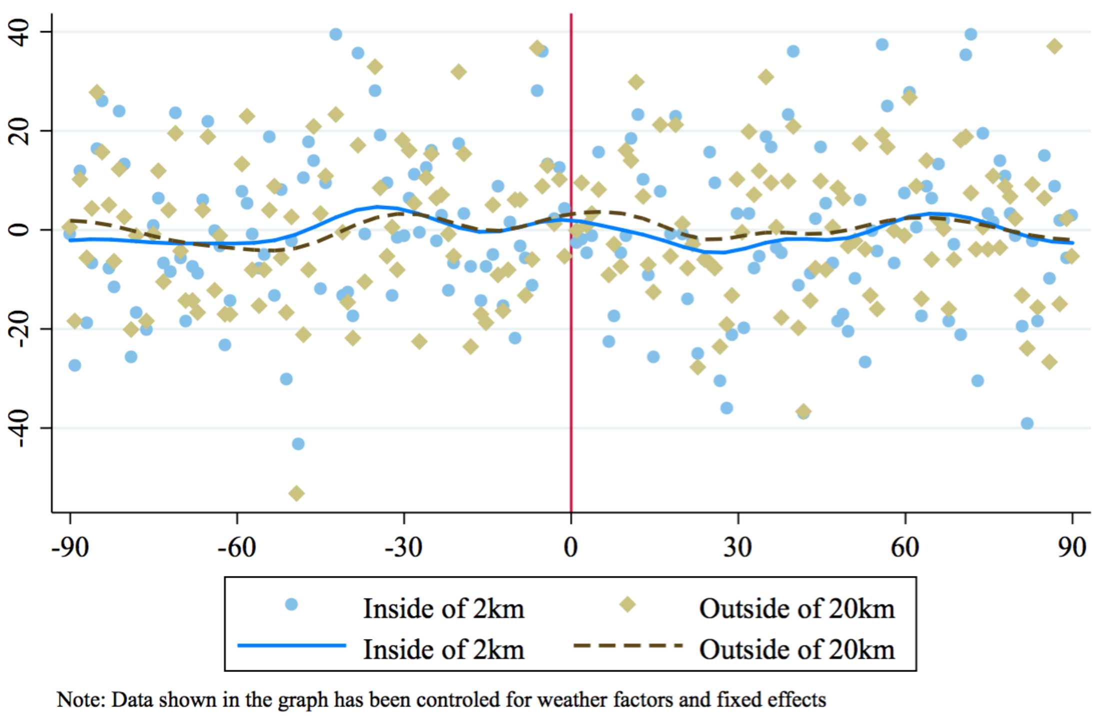


Figure 8. Average Effect of Subway Opening on API (%) in 90-weekday Window For Monitors Inside of 2km Vs. Outside of 20km

Figure 8 extends the time window to 90-weekday and also shows the average environmental effect of subway openings when using monitors outside of 20km as control group. We can see that, after the 60th weekday post-opening, the trend goes back to be similar to the trend before opening, and the effect fades out. The difference between the coefficients in Column (2) and (3) also serve as an evidence. This is reasonable because after a certain amount of time, automobile commuters from other areas will adjust their route to take the roads with less traffic volume, which is the area near the newly opened subway line. Then the traffic volume is increasing gradually, causing the decrease in the environmental effect. However, with the preliminary results from Table 5, it is difficult to tell how the transportation behavior changes in different time after the subway opens. Also from the standard DD with three time windows, it is hard to tell the relationship between the change in the environmental effect and the change in days after opening. In order to make the story clearer, we extend the standard DD to cover more variation in both time and distance.

4.3 Extension of Standard DD

4.3.1 DD with Continuous Measure of Time

$$y_i = \theta_0 + \theta_1\, After_t + \theta_2\, Within2_{it} + \theta_3\, [After_t \times Within2_{it}] \qquad (3)$$

$$+\theta_4 \boldsymbol{x}_t + \xi_t + \upsilon_i + \varepsilon_{it}$$

Different from the standard DD, we take one step further and replace the time indicator for subway opening with a continuous variable $After_t$ which takes the value of zero for all dates before subway opening, and continuous numbers of days for dates after the opening date. The interaction term in turn is replace with $After_t \times Within2_{it}$. Figure 7 shows clearly the fluctuation in the environmental effect of subway expansion at different points of time, that is why we replace the dummy time indicator with a continuous measurement, to catch more variation. Assume the the impact of subway expansion on ln(API) is linear in time, θ_3 then captures the difference in the effect between two groups for one more day after the subway opens. Assume the magnitude of the effect is linear to the number of weekdays after opening, we can see that for 30-weekday window, with one more weekday passing, the API will reduce by 0.41% more. By simple calculation, we can get the maximum reduction effect after 30 weekdays, which is 12.3%. However, for the 60-weekday window, the magnitude of parameter is very small, closed to zero, and not significant at any level.

Table 6. The Effect of Subway Opening on API (%):DD with Continuous Time Measurement

Ln(API)	30 Days (1)	60 Days (2)
# weekdays after opening * 1(Distance<=2km)	-0.00413**	- 0.00002
	(0.0016)	(0.0003)
Constant	4.5564 ***	5.9268***
	(0.5621)	(0.3648)
Observations	3729	7367
R-squared	0.701	0.654

Note: Each column reports the result from one regression. All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. Column 1, 2 report the coefficient estimates by using monitors outside of 20km as control group, and using 30 and 60 weekdays window respectively.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

This result demonstrates two points. First, the pollution reduction effect is not linear to the number of weekdays after opening. Otherwise, the 30-weekday parameter should be about twice of the 60-weekday parameter in magnitude. Second, the trend of the environmental effect does differ at different time points after the subway opens. Because of the significant effect showed in Table 6, even though the impact of days post-opening is nonlinear, we have the confidence that, during different time periods, commuters have behavior adjusted differently to adopt the new subway lines. In the subsection 4.3.3 below, we relax this linear assumption in the number of weekdays, and generate the trend of the environmental effect during different time periods post-opening.

4.3.2 Heterogeneity in Treatment Group

The results above have demonstrated the significant effect that subway expansion has on reducing air pollution within a certain time period. In this subsection, we examine whether there is any heterogeneity in the effect caused by the difference in the distances. For the five subway lines, there are eight monitors that are located within 2km, and each monitor has a different location. In order to account for the variation in distance within the treatment monitors, we include the $Distance_{it}$ variable into the standard DD specification in equation (1), and interact it with the treatment indicator $Within2_{it}$. The new specification with heterogeneity in the treatment group is now shown in equation (4),

$$\ln(API)_{it} = \theta_0 + \theta_1\, Open_t + \theta_2\, Within2_{it} + \theta_3\, [Open_t \times Within2_{it}]$$

$$+\theta_4\, [Within2_{it} \times Distance_{it}] + \theta_5\, [Open_t \times Within2_{it} \times Distance_{it}] \qquad (4)$$

$$+\theta_6 \boldsymbol{x}_t + \xi_t + \upsilon_i + \varepsilon_{it}$$

We assume that the closer a monitor is to the new subway line, the larger it will be affected. Thus to make the interpretation easier and more intuitive, we transfer the distance to the inverse distance ($2\text{km} - Distance$). With this specification, the effect of subway opening on API will be captured jointly by $\theta_3\ and\ \theta_5$. The estimation results are presented in Table 7 below. If the effect of distance is linear on the pollution reduction effect, we can assume the distance to be 0km, 1km and 2km, and get the joint effect simply by plugging in the numbers and basic calculation.

Table 7. The Effect of Subway Opening on API (%):DD with Heterogeneity in Distance

Ln(API)	60 Days
1(Open) * 1(Distance<=2km)	0.00239
	(0.0473)
1(Open) * 1(Distance<=2km) * (2km-distance)	-0.116***
	(0.0399)
0 Km	-0.2299***
	(0.0526)
1 Km	-0.1138***
	(0.0302)
2 Km	0. 0024
	(0.0473)
Observations	7,367
R-squared	0.651

Note: All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. The second part presents the joint significance of θ_4 *and* θ_5 in equation(4) assuming distance is linear.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

From Table 7, we can clearly get the linear effect when we assume the monitor is located right at the subway line 0 km, 1km away or 2km away. The results are very intuitive because the table shows that the further the treatment monitor is located, the smaller the reduction effect is, which is exactly what we have expected. If the monitor is located right at the newly opened subway line, the effect on air pollution is -23% and significant at 99% level. However, if the monitor is located right at the 2km boundary, the effect of subway opening on API is a 0.02% increase and insignificant. Two points are revealed from this result. First, as stated before, in reality the places where some subway stations are located, are probably to be the places with the worst traffic due to the large travel demand, that is why when the subway line opens, the traffic volume will reduce the most.

The second point is that, as the monitor's location getting further by 1km, the change in the pollution reduction effect is not in a linear trend. To figure out the heterogeneous effect of distance, we still need to loose the linear assumption which we discuss in the next subsection.

4.3.3 Nonparametric Method

To relax the linear assumption in analyzing the time effect and the spatial effect of subway expansion, we use a nonparametric method to cover the variation caused by difference in time after opening and the difference in distances. To do that, we simply replace the continuous measurement of time or distance with a set of dummy variables to cover each time period or distance range.

Time measurement as dummy variables – We use the 60 weekdays window, and separate it into six time periods, each includes 10 weekdays after the subway opens. Similar to the regression model in 4.2, instead of the six time dummies before opening, we interact the six time dummies after opening with the indicator for the treatment group. The regression results are presented in the form of image in Figure 8. The graph shows the coefficients and their 95% Confidence Intervals. This graph gives more detailed information than the results we get in 4.3.1 with the continuous measurement of time, and shows a similar trend with the graph we draw from raw data.

The trend we can tell from Figure 8 is that the pollution reduction effect is nonlinear to the number of weekdays after opening, the reduction effect achieves the maximum of 17% during the first 10 weekdays, and decreases until the 30th weekday. During the 30-

40 weekdays, the reduction effect bounces back a little and then decreases again, and becomes less significant.

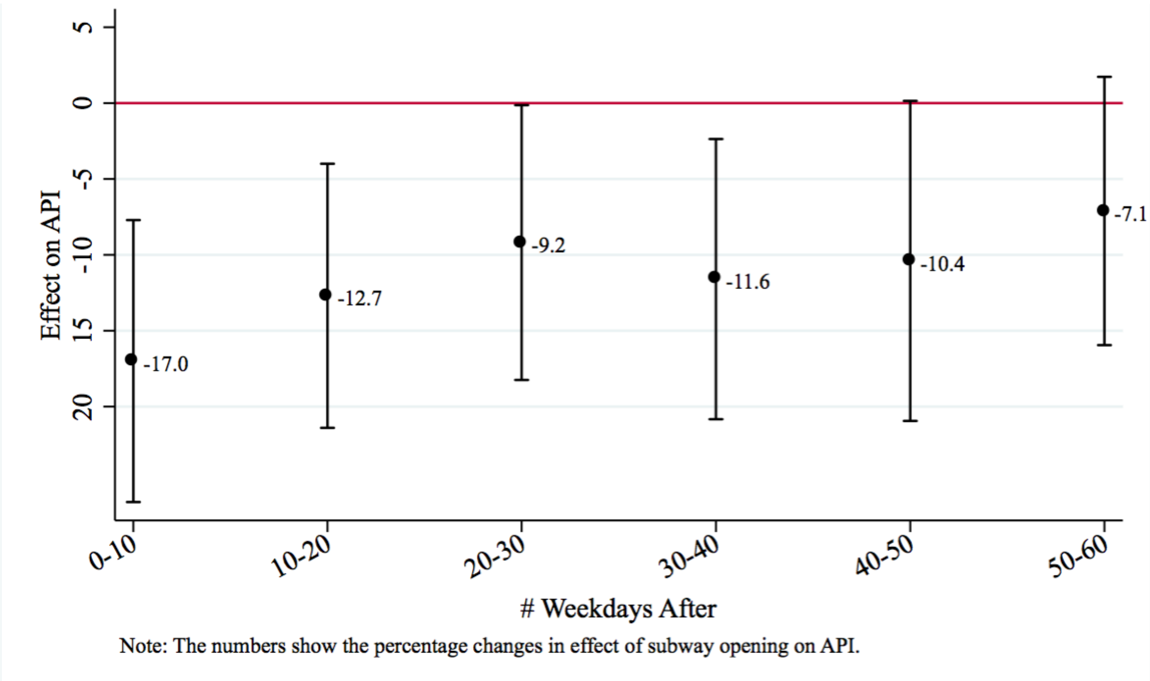


Figure 9. Effect of Subway Opening on API (%) in Different Time Periods After Subway Opening, for Monitors inside of 2km Vs. Outside of 20km

After 50 weekdays, the effect becomes insignificant. This estimation graph also indicates some patterns in the adjustment of commuters' travel behavior. We can regard them as a process of "realize" and "adjust". During the first 30 weekdays, when a new subway line opens nearby, a considerable amount of commuters takes the subway instead of driving the cars. The number of cars reduces and brings better air quality. As other drivers realizing that the area is much easier to drive through, more drivers will adjust their route and take the advantages. That will explain the decreases in the reduction effect. Then after 30 weekdays, drivers realize that the traffic in this area is not as smooth as expected, a certain amount of them will switch to other route or take the public transportation, which we cannot tell, and reduce the traffic again but in a smaller amount. After the two process of "realize" and "adjust", the transportation condition in this area will gradually return to a normal status, the pollution reduction effect of the new subway line fades out too. This is the story we can tell from the environmental effect of subway opening. In order to testify the exact adjustment of commuters' travel behavior, we would need more data and analysis on the subway ridership and traffic volume.

Distance measurement as dummy variables – To relax the linear assumption we use in the estimation of the heterogeneous effect of distance, we replace the treatment indicator *Within2* with nine distance dummy variables. Each dummy variable takes the value of one if the monitors that are located within the certain 1km distance range. The control group we use is still the monitors outside of 20km.

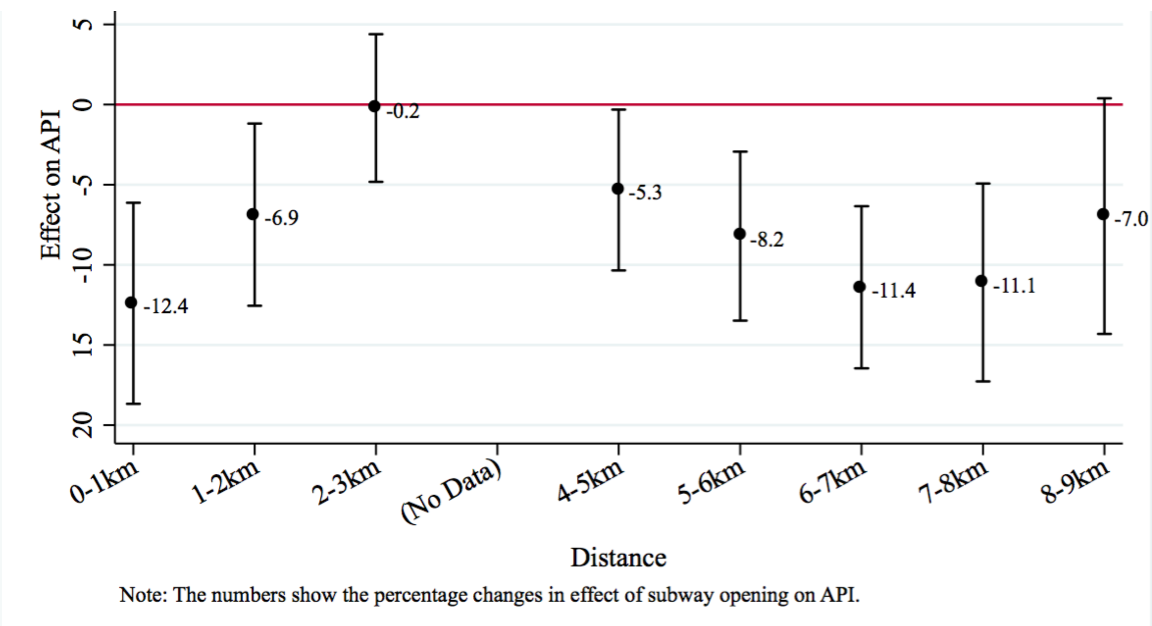


Figure 10. Effect of Subway Opening on API (%) for Monitors Located at A Certain Distance away from the Subway Lines, with Monitors outside of 20km as Control Group

From Figure 10, we can see that the heterogeneous effect of distance is clearly not linear, the API captured by monitors within 0-1km distance from the subway lines is reduced the most significantly, and the reduction effect maximizes as 12.4%. The API captured by monitors within 2-3km and 8-9km distance are not significantly decreased. For the rest of the monitors, the API decreases significantly. These estimation results can serve as a good evidence that there exist many unobservable factors that can influence monitors in the buffer zone we define above. That is why we leave out the confusing monitors. Taking the monitors outside of 20km as the control group, we can see that, as the monitor's distance to the subway line increases, the environmental effect of subway opening is basically in an inverted U-shape. This may also give us a sense of the benefited area of a new subway line, and how does the subway system contribute to a better traffic condition in different areas.

So far, we present the results from standard DD, DD with continuous time measurement, the heterogeneous effect of distance and the nonparametric estimation. The significance of the pollution reduction effect of subway expansion has far been demonstrated. The significant effect that distance has on the magnitude of the environmental effect is testified as well. We also prove that in different time period after opening, the environmental effect of subway expansion is different. In the next section, we will discuss the drawbacks, the policy implications and future extensions of this study.

5 Discussion

After finding out the statistical significance of the environmental benefit effect contributed by subway expansion, it is also necessary to discuss the economic significance of the environmental effect, and how can our study contribute to the policy. Before discussing possible drawbacks in our specifications, we first examine the economic significance of the environmental effect of the subway.

5.1 Economic Significance

To examine the economic significance of the pollution reduction effect, we need to consider both the benefit on human health, and the implied benefit of the traffic diversion effect on automobile travel. For now, we discuss the first part. In the future research, when we add the traffic data into this study, the benefit in reducing the external cost of traffic congestion will be further discussed.

How large is the reduction effect on API in economic terms – As we introduced above, the major air pollutant of Beijing's air pollution is the particulate matters, PM10. According to a report about the health effect of particulate matter released by WHO for European countries, all-cause daily mortality is estimated to increase by 0.2–0.6% per 10 μg/m^3 of PM10. Take the 20.9% reduction effect within a 30-weekday window as an example. Suppose the PM10 density is in the 0.150-0.350 mg/m^3 range (API is in 100-200 range), and PM10 is the major pollutant of the day. Based on the transform of the calculation equation of API, the density of PM10 can be expressed by

$$\text{PM10 density} = [\ (\text{API}-100) * (0.35-0.15) / (200-100)] + 0.15$$

If the API decreases by 20%, then the PM10 density will decrease by more than 20%, around 23% to 26%. We can see that per 0.01 mg/m^3 will increase the daily mortality by 0.2-0.6%, then a more than 20% reduction in PM10, which is about 0.03-0.07 mg/m^3, will significantly reduce the mortality. Although this is just a rough calculation based on one specific example, we can clearly get that the opening of a subway line does benefit greatly to the society in terms of human health. However, there surely are many limitations in our approximation of the economic significance. We only use the example given by WHO about the mortality rate and PM10. There must be other uncounted health effects such as the effect on certain types of diseases. Also, it is possible that the effect of PM10 on health in China is different from the effect in the area that the WHO reports on. That is why we may not compare this result with literatures about the health consequences of air pollution in other countries. Overall, our estimation of the economic significance of the subway opening in terms of the benefit to human health may represent a lower bound of the total health benefit, more detailed information is needed if we would like to get an accurate estimation.

5.2 Drawbacks and Future Extensions

Our analysis is based on the assumption that, in absence of the subway expansion, the trend of API captured by both groups of monitors should be similar during the short time window around the subway openings. This assumption is reasonable since most of the confounding factors such as the weather conditions, policy interventions, and the polluting factories have been controlled by our DD specification. However, it is instructive to consider the possible threats to our identification.

First of all, plans for subway location have uncontrollable factors. It is common in the city and regional planning that public transportation infrastructures should be distributed to the area with the largest travel demand. This unmeasurable fact may lead to the correlation between the subway location and the traffic volume around it, which means we may underestimate the environmental effect of subway opening. Because even though the subway diverts some commuters away, if the travel demand is too large, the effect of the reduction in automobile travel is sill too week to be captured. One possible way to capture this effect is to combine our study with detailed information about the different districts of Beijing, including the population, income and car ownership. By adding in the information above, we will get the heterogeneous effect for each of the five subway lines according to the district or the specific area that each line passes through.

The second drawback lies in the basic institutional setting of our study, which is that the subway expansion will reduce the automobile travel, and in turn reduce the transportation originated air pollution. The reason we think our estimation results are not strong enough is the lack of evidence of the middle part of this setting. In the next step, we will combine this study with the traffic congestion data. By doing this, we can testify our assumption that subway expansion diverts automobile travelers away from their vehicle to public transit. Also, we may calculate out the percentage that automobile contributes to the air pollution.

6 Conclusion

During the past decades, China has undergone dramatic economic growth, especially in the automobile market. At the same time, the air pollution issue worsens in Beijing, the capital city. Transportation sector has been well recognized as a major source of air pollution. However, the literature of the correlation between public transportation and air pollution is limited. We seek to contribute to the current literature by conducting this spatial analysis to quantify the causal effect of Beijing subway expansion on air pollution.

In this study, we collect the monitor level Air Pollution Index data to represent the daily air pollution levels in Beijing. Different from the existing literature which uses the discontinuity in subway ridership around the opening date, we focus on the spatial differences in subway lines and air pollution monitors, and use the distance between them as our identification. By controlling weather conditions, driving restrictions and fixed effects, we successfully tease out the significant positive effect the subway opening contributes to the improvement of air quality in Beijing.

Focusing on the effect of the opening of five Beijing subway lines between 2008 and 2012, we find that the opening of new subway stations reduces API significantly. The API measured by the treatment group decreases by 20.9% after the subway opens within 30 weekdays window. The effect reaches its maximum at the first 10 weekdays after opening, and tends to fade out after 60 weekdays, which might be explained by the adjustment of the commuters' travel behavior.

Our results can serve as a good evidence for the situation of behavioral response when a new subway line is opened. In the future, there are several extensions we can focus on.

First, we may replace the API data with more specific air pollutants' density. This can direct us to specific pollutants that are correlated the most with commuters' travel behavior, so that we can analyze the behavioral response better. Second, we may combine our study with the traffic data such as traffic congestion index and traffic volumes. This can provide evidence for the correlation between public infrastructure and demand for automobile travel.

In the future, this study can be applied to evaluate the environmental effects of other public transit such as bus and light rail. Also, we can extend this study to other cities in China which also experience rapid expansion in their public transit system. One further step would be controlling of the specific city characteristics, and capture the aggregate effect of public infrastructure on air quality for the entire country.

Reference:

1. Currie, J., & Walker Reed. (2011). Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, *3*(1), 65–90.
2. "China's Automobile Market". Accenture Research Analysis. IHS Auto Insight April 2013;
3. Gabe Collins and Andrew Erickson, "Counting Cars: Rising Private Automobile Ownership in Chinese Cities Paves Road for Gasoline Demand," *China SignPost*™ (23rd June, 2013).
4. Mohring, H. (1972). OPTIMIZATION AND SCALE ECONOMIES by. *American Economic Review*
5. Vickrey, S. W. (1969). Congestion Theory and Transport Investment. *The American Economic Review*, *59*(2).
6. Duranton, B. G., & Turner, M. A. (2011). Fundamental Law of Road Congestion: Evidence from U.S. Cities. *American Economic Review*, *101*(October)
7. Chen, Y., & Whalley, A. (2012). Green Infrastructure: The Effects of Urban Rail Transit on Air Quality. *American Economic Journal: Economic Policy*, *4*(1), 58–97.
8. Viard, V. Brian and Shihe Fu. 2011. "The Effect of Beijing's Driving Restrictions on Pollution and Economic Activity". MPRA Paper 33009, University Library of Munich, Germany.
9. Li, S., Xiao, J., & Liu, Y. (2014). The Price Evolution in China' s Automobile Market. *Journal of Economics & Management Strategy*, *24*(January), 1–44.

10. Chen, Y., Jin, G. Z., Kumar, N., & Shi, G. (2013). *The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality*. *Journal of Environmental Economics and Management* (Vol. 66)
11. Davis, Lucas W. 2008. "The Effect of Driving Restrictions on Air Quality in Mexico City". Journal of Political Economy, vol. 116, 38 – 81.
12. Anderson, M. Subways, Strikes, and Slowdowns: The Impacts of Public Transportation on Traffic Congestion. *American Economic Review*, *104*(9), 2763–2796.
13. Schlenker, W. and W. R. Walker (2012). "Airports, Air Pollution, and Contemporaneous Health," NBER working paper #17684.
14. Hanna, R. and P. Oliva (2011). "The Effect of Pollution on Labor Supply: Evidence from a Natural Experiment in Mexico City," NBER Working Paper #17302
15. Lin, C.-Y. Cynthia,Wei Zhang, and Victoria I. Umanskaya. 2011. "The Effects of Driving Restrictions on Air Quality: São Paulo, Bogotá, Beijing, and Tianjin". Agricultural and Applied Economics Association 2011 Annual Meeting. 2011.
16. WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide (Global update 2005, Summary of risk assessment).
17. Should Urban Transit Subsidies Be Reduced? By Ian W. H. Parry and Kenneth A. Small* American Economic Review 2009
18. Wheels of Fortune: Subway Expansion and Property Values in Beijing
Shanjun Li, Jun Yang, Ping Qin, Shun Chonabayashi1
19. World Health Organization (2013). Health effects of particulate matter.

Appendix A: Using (>10km) As the Control Group

Table 1. The Effect of Subway Opening on API (%): Standard DD Estimates (10KM)

Control Group:	>10km	>10km	>10km	>2km
	(1)	(2)	(3)	(4)
Ln(API)	DID (30Days)	DID (60 Days)	DID (90Days)	DID (30 Days)
1(Distance<= 2km)	0.0650***	0.0332**	0.0243**	0.0444***
	(0.0233)	(0.0147)	(0.0114)	(0.0152)
1(Subway Opening)	0.0219	0.0286	0.00981	0.0163
	(0.133)	(0.121)	(0.108)	(0.134)
1(Open) * 1(Distance<=2km)	-0.132***	-0.0790***	-0.0548***	-0.105***
	(0.0313)	(0.0216)	(0.0171)	(0.0226)
Constant	4.394***	5.958***	6.133***	4.424***
	(0.547)	(0.358)	(0.231)	(0.552)
Observations	4,924	9,715	14,526	5,835
R-squared	0.705	0.656	0.640	0.708

Note: Each column reports the result from one regression. All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. Column 1-3 report the coefficient estimates by using monitors outside of 10km as control group, and using 30-Weekday window, 60-Weeksay window and 90-Weekday window respectively. Colum 4 reports the coefficient estimates by using monitors outside of 2km as control group and in 30-weekday time window.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2. The Effect of Subway Opening on API (%):DD with Continuous Time Measurement (10KM)

Ln(API)	30 Days (1)	60 Days (2)
# weekdays after opening * 1(Distance<=2km)	-0.00364***	-0.000289
	(0.00135)	(0.000466)
Constant	4.507***	5.927***
	(0.555)	(0.347)
Observations	4,924	9,715
R-squared	0.705	0.659

Note: Each column reports the result from one regression. All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. Column 1, 2 report the coefficient estimates by using monitors outside of 10km as control group, and using 30 and 60 weekdays window respectively.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 3. The Effect of Subway Opening on API (%):DD with Heterogeneity in Distance (10KM)

Ln(API)	60 Days
1(Open) * 1(Distance<=2km)	0.00557
	(0.0385)
1(Open) * 1(Distance<=2km) * (2km-distance)	-0.0954***
	(0.0357)
0 Km	-0.1852***
	(0.0445)
1 Km	-0.0898***
	(0.0215)
2 Km	0. 0056
	(0.0394)
Observations	9,715
R-squared	0.656

Note: All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. The second part presents the joint significance of θ_3 and θ_5 in equation(4) assuming distance is linear.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

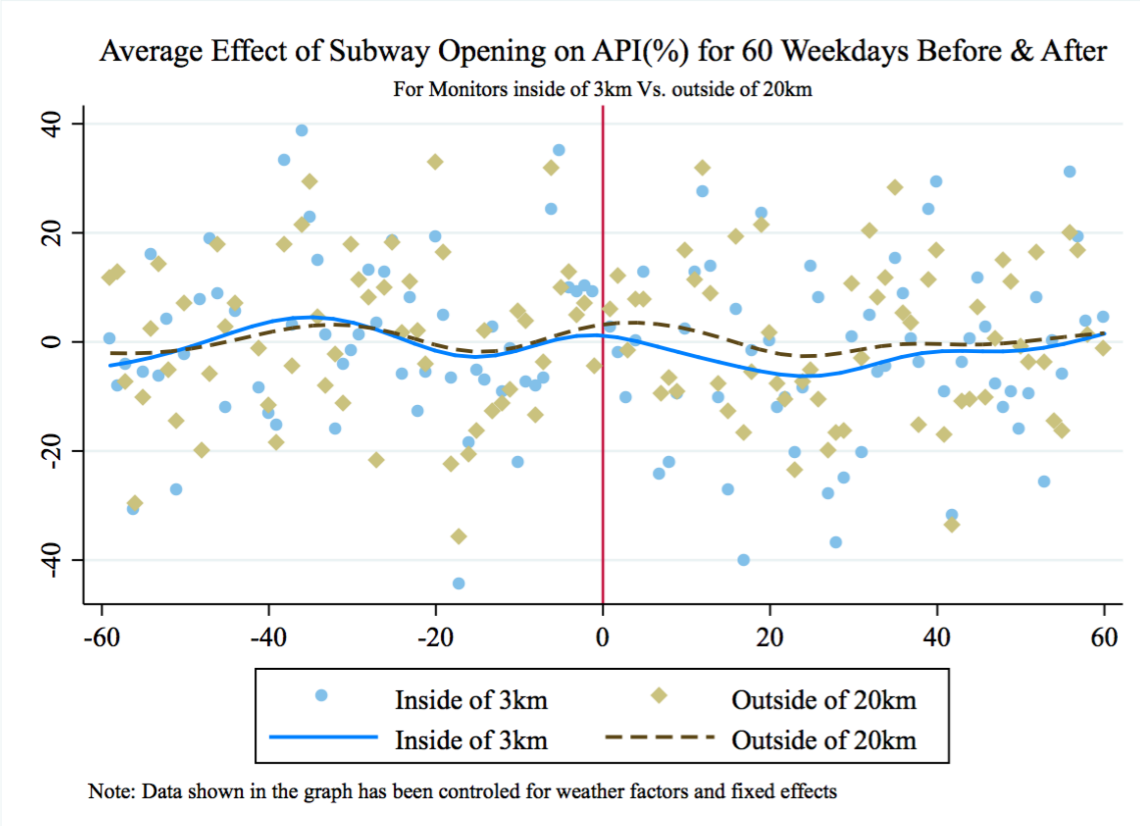
Appendix B: Using Different Treatment Groups

Table 1. The Effect of Subway Opening on API (%): Standard DD Estimates

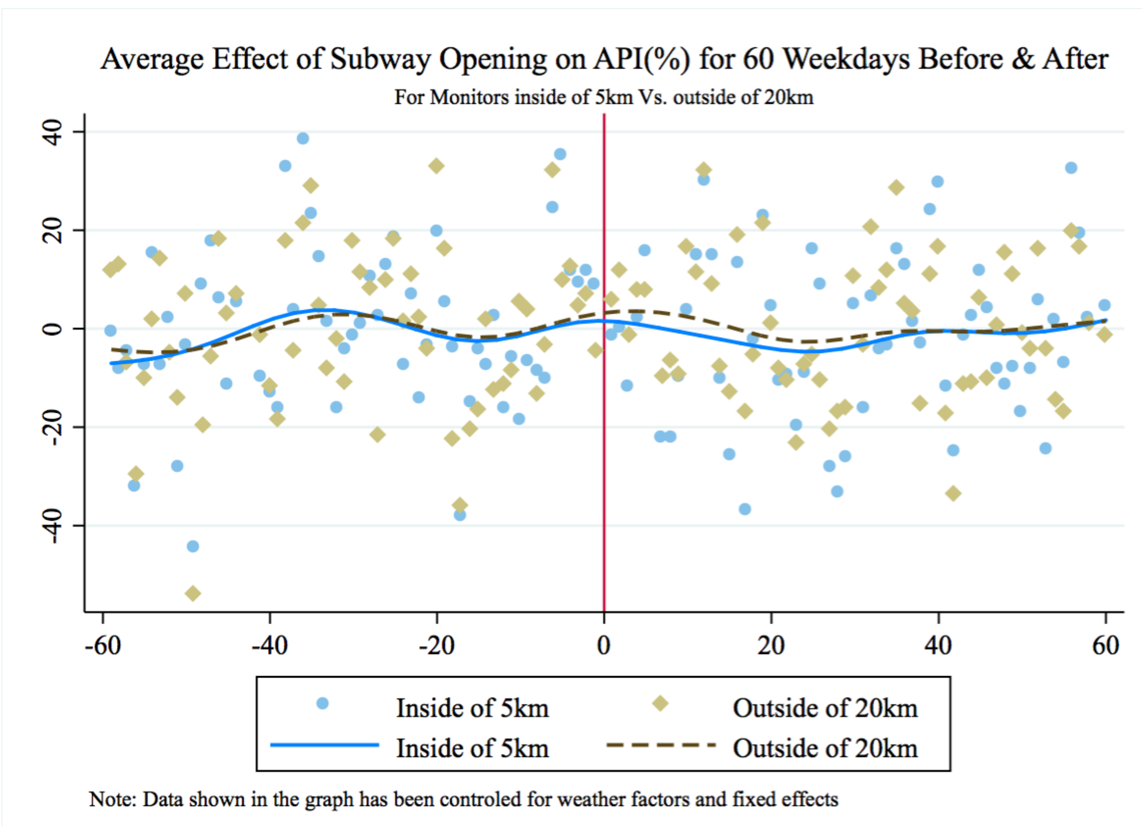
Treatment Group #km :	< 3km (1)	< 5km (2)	<8km (3)
Ln(API)	DID (30Days)	DID (30 Days)	DID (30Days)
1(Distance<= #km)	-0.0199	-0.0229	0.0356
	(0.0322)	(0.0315)	(0.0244)
1(Subway Opening)	0.0384	0.0290	0.0216
	(0.129)	(0.129)	(0.129)
1(Open) * 1(Distance<= #km)	-0.166***	-0.145***	-0.119***
	(0.0352)	(0.0338)	(0.0263)
Constant	4.471***	4.503***	4.502***
	(0.550)	(0.551)	(0.554)
Observations	3,777	3,934	4,364
R-squared	0.702	0.702	0.704

Note: Each column reports the result from one regression. All have controlled for the monitor FE, year-month FE, Day of week FE, weather variables, lagged weather variables and driving restriction dummies. Cluster SE by each day in parenthesis. Column 1-4 report the coefficient estimates by using monitors inside of 3km, 5km, 8km and 10km as treatment group respectively, using 30-Weekday window and monitors outside of 20km as control group.

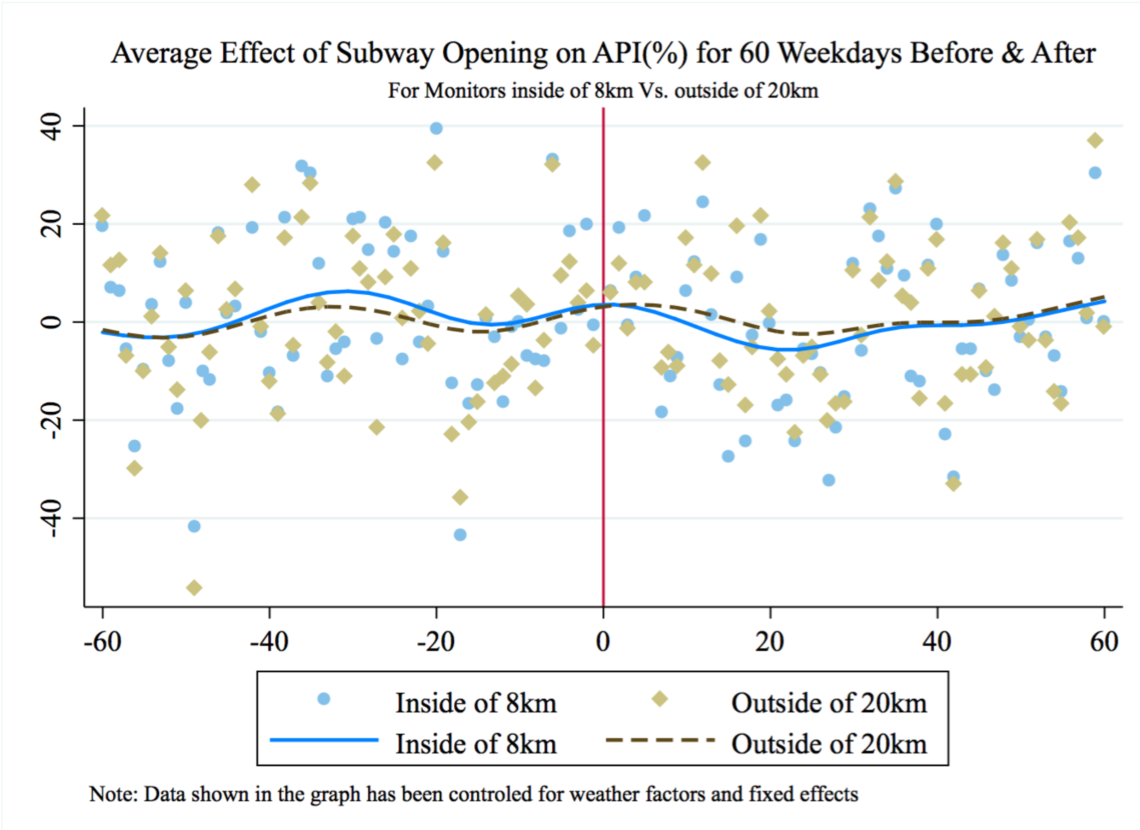
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.



Average Effect of Subway Opening on API(%) for 60 Weekdays Before & After
For Monitors inside of 3km Vs. outside of 20km
40
20
0
-20
-40
-60
-40
-20
0
20
40
60
Inside of 3km
Outside of 20km
Inside of 3km
Outside of 20km
Note: Data shown in the graph has been controled for weather factors and fixed effects



Average Effect of Subway Opening on API(%) for 60 Weekdays Before & After
For Monitors inside of 5km Vs. outside of 20km
40
20
0
-20
-40
-60
-40
-20
0
20
40
60
Inside of 5km
Outside of 20km
Inside of 5km
Outside of 20km
Note: Data shown in the graph has been controled for weather factors and fixed effects


Average Effect of Subway Opening on API(%) for 60 Weekdays Before & After
For Monitors inside of 8km Vs. outside of 20km
40
20
0
-20
-40
-60
-40
-20
0
20
40
60
Inside of 8km
Outside of 20km
Inside of 8km
Outside of 20km
Note: Data shown in the graph has been controled for weather factors and fixed effects

Appendix C: Supplementary Graphs

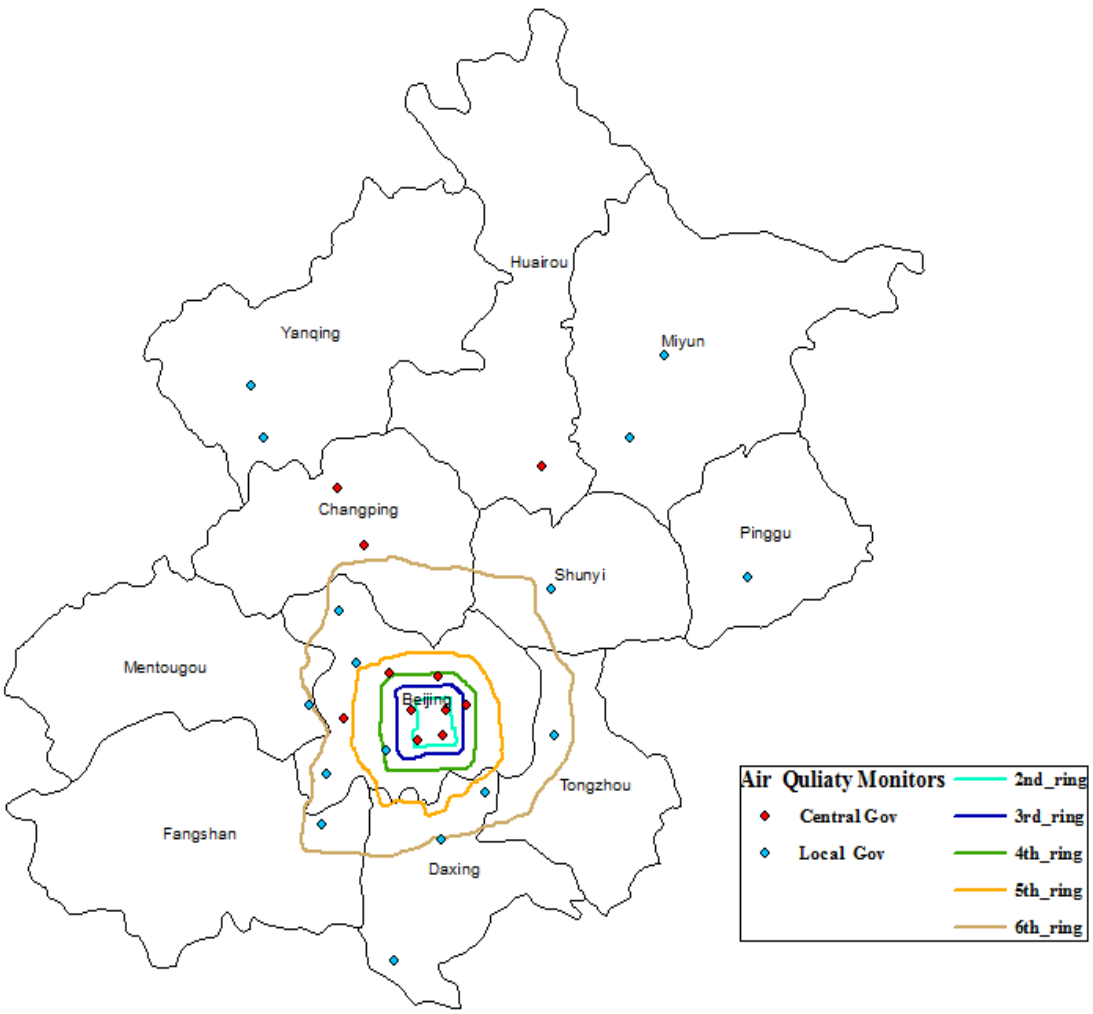


Figure 1. Air Quality Monitors & Ring Roads in Beijing

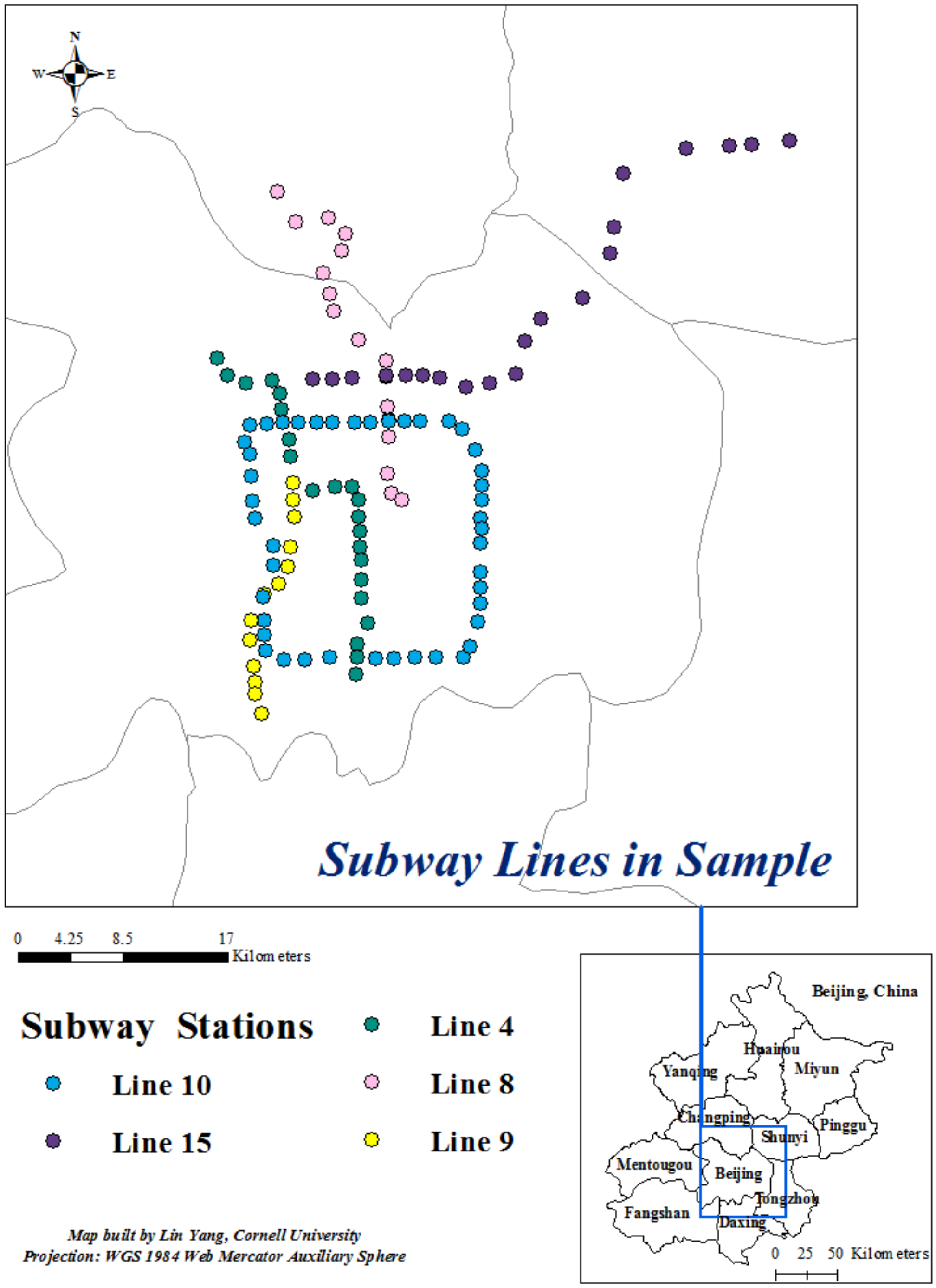


Figure 2. Subway Lines in Sample

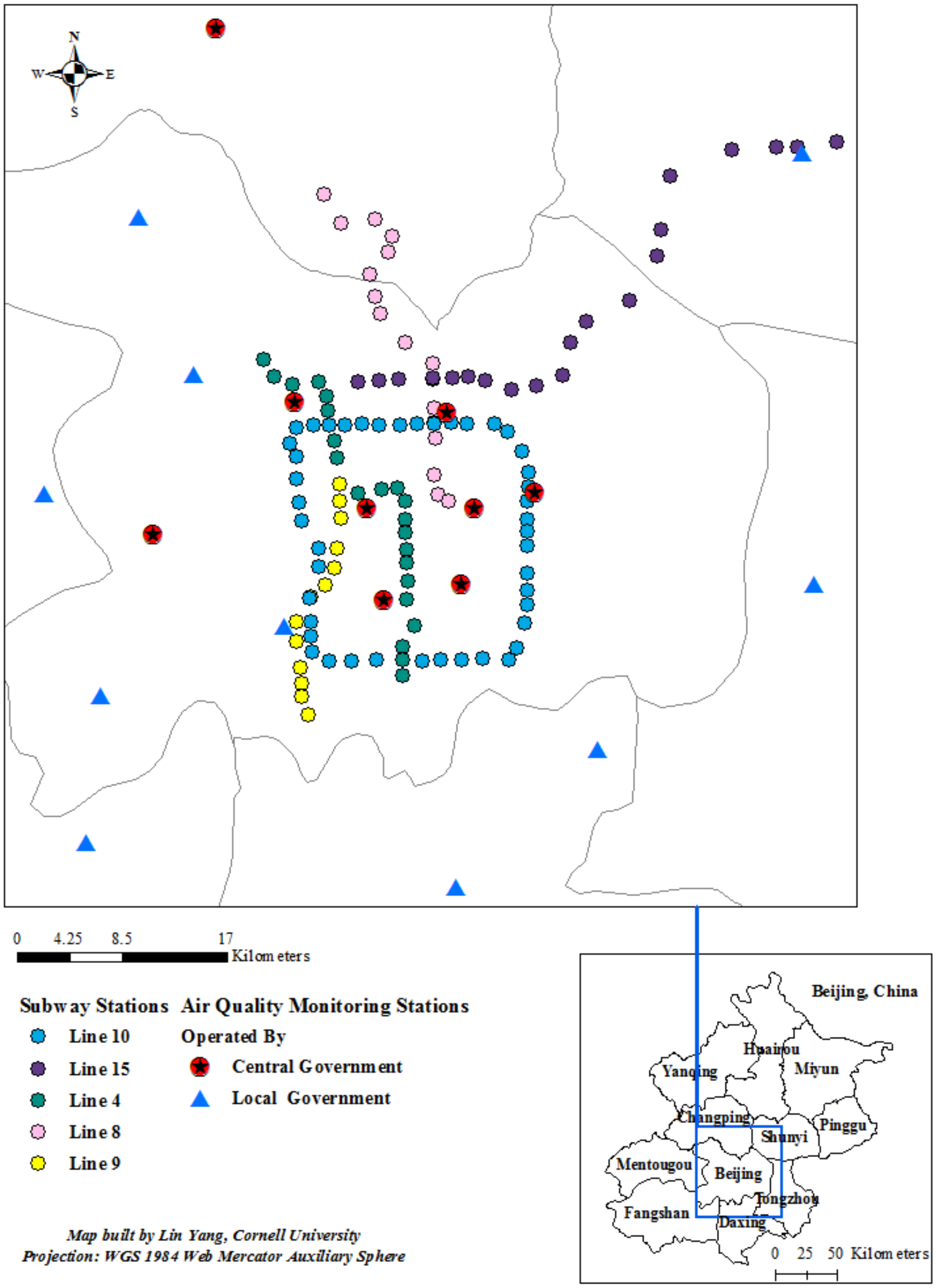


Figure 3. Sample Subway Lines & Air Pollution Monitors